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REFINEMENT AND VALIDATION OF TWO
DIGITAL MICROWAVE LANDING
SYSTEM (MLS) THEORETICAL MODELS

BY

WILLIAM G. DUFF

AND

CHARLES R. GUARINO

Prepared Under Contract No. NAS 1-13683

FOR

NATIONAL AERONAUTICS AND SPACE ADMINISTRATION

AUGUST 15, 1975

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Atlantic Research Corporation
EMM Department
5390 Cherokee Avenue
Alexandria, Virginia 22314

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FOREWORD

This report was prepared for the National Aeronautics and Space Administration, Langley Research Center, by Atlantic Research Corporation under Contract Number NAS1-13683.

The project was performed under the technical direction of William G. Duff at Atlantic Research, and Richard M. Hueschen of NASA Langley. Other contractor personnel who contributed directly to this project include:

Charles R. Guarino]	Atlantic Research Corporation
David J. Hyduke		

Other personnel who participated in this project include:

Thomas M. Walsh	NASA Langley
Nesim Halyo	University of Virginia

ABSTRACT

This report describes the results of an effort to refine and validate two digital microwave landing system theoretical models developed under NASA Contract No. NAS1-1192. The MLS models being considered are generic models for the Doppler and scanning-beam frequency reference versions of the MLS. These models represent errors resulting from both system noise and discrete multipath. The data used for the validation effort were obtained from the Texas Instrument conventional scanning beam and the Hazeltine Doppler feasibility hardware versions of the MLS.

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List of Symbols

$X(t)$	Time domain representation of MLS errors
$X_T(t)$	Function $X(t)$ limited to values $-T \leq t \leq T$
$X_T(j\omega)$	Fourier transform of $X_T(t)$
$S(\omega)$	Spectral density of $X(t)$
$U_{T/2}$	Spectral Window
a 's & b 's	Coefficients resulting from curve fitting
$H(j\omega)$	Transfer Function resulting from curve fitting
$\phi(\tau)$	Autocorrelation function
$\phi(m)$	Discrete form of Autocorrelation function
Γ	Standard deviation of MLS errors
α	Reciprocal of correlation time

1.0 Summary and Suggested Studies

A program is in progress to develop an advanced universal Microwave Landing System (MLS) which is intended to eventually replace the present-day Instrument Landing System. The MLS consists of azimuth and elevation antenna systems, and Distance Measurement Equipment (DME) at the runway and corresponding airborne receiving equipment to provide position and velocity navigation data for terminal area flight operations. Insofar as Conventional Take-off and Landing (CTOL) operations are concerned preliminary design and system integration have been carried out by RTCA[7]. This preliminary design included siting arrangements of the ground equipment, volume of coverage and format of the signals, and accuracy standards for the combined ground-based and airborne equipment. Although an effort has been made to specify the maximum range and angle error, the statistical characteristics of the MLS errors are basically unknown.

Computer simulation models that represent both the system noise and discrete multipath MLS errors were developed and implemented under NASA Contract NAS1-11992. Generic models were developed for frequency-reference scanning-beam and Doppler systems. These models were developed from theoretical considerations concerning the communication channel.

The generic model developed for system noise was represented in terms of an autocorrelation function which was given in discrete form by

$$\phi(m) = \Gamma^2 e^{-\alpha T|m|}$$

For the purpose of the modeling effort under NAS1-11992, Γ was taken as the standard deviation of the elevation or azimuth error as given by the RTCA specifications for the MLS, and the correlation time (α^{-1}) was varied to determine the effect on aircraft performance.

The model for discrete multipath errors resulted from applying Green's Theorem to determine the field arising from an electromagnetic wave which is reflected and scattered from an object such as a hangar or aircraft. The resulting discrete multipath errors are a function of the geometry of the multipath configuration as presented in Section 3.7.

The objective of the present contract was to validate and refine these models by comparing and correlating the computer generated MLS signals with MLS signals measured from flight data. The data used in the study were obtained on the Texas Instrument conventional scanning-beam and the Hazeltine Doppler systems. Figure 1 illustrates the test site locations for the Hazeltine and Texas Instrument microwave landing systems at Wallops Island. The test flight path from which the data was obtained was for a straight in approach with a 3° glideslope.

For the purpose of this validation effort, MLS errors were considered to consist of system noise, which could be considered as a stationary random process, and discrete multipath errors, which result in a nonstationary random process. The experimental data for the system noise were used to obtain parameter

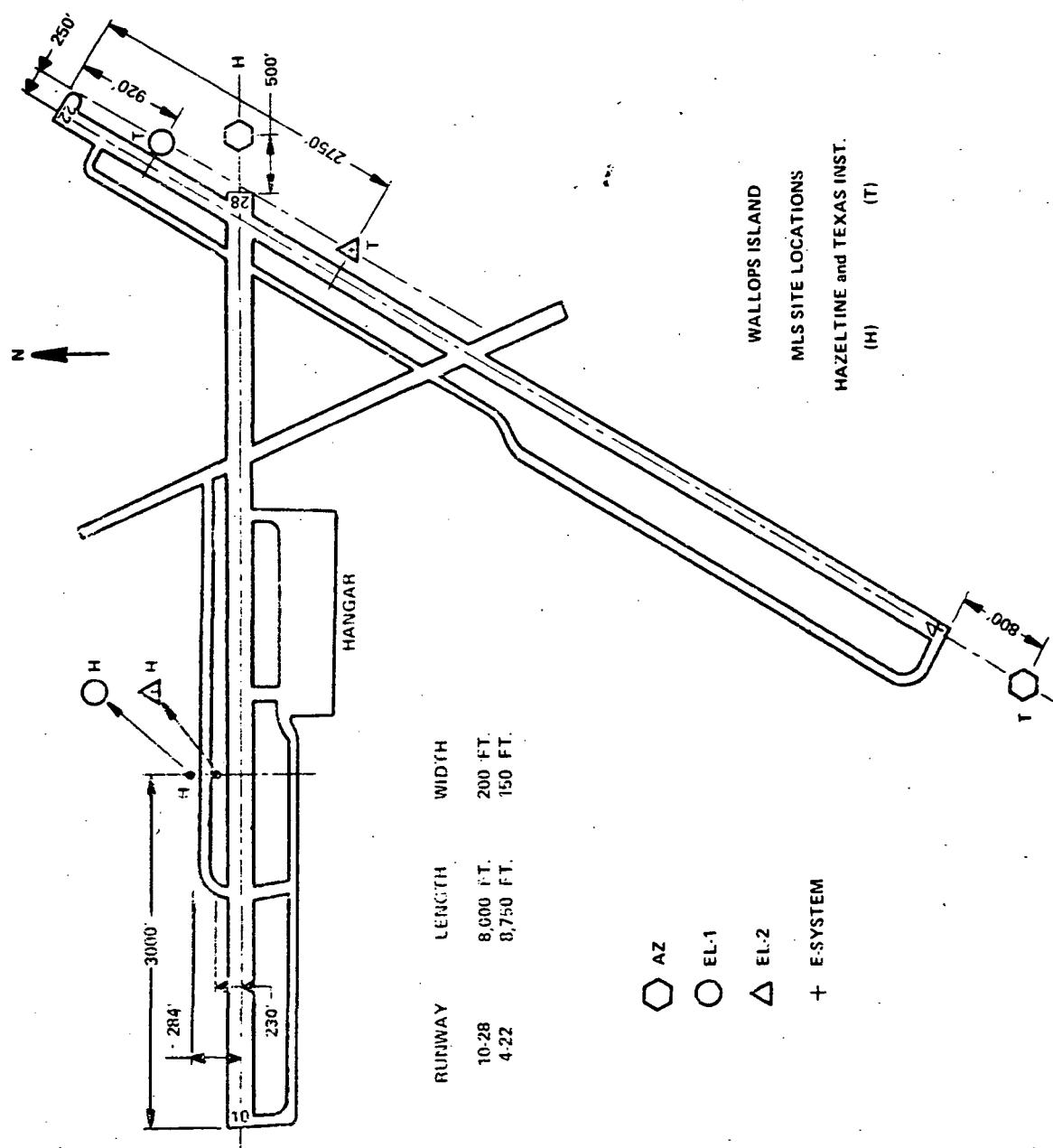


Figure 1. Wallops Station MLS Test Site Locations.

estimates and these were compared with the theoretical model. The best fit models obtained from analyzing the experimental data resulted in the same form for the noise error model as that obtained from theoretical considerations, and this is considered to provide sufficient validation for the form of the generic error model which is

$$\phi(m) = \Gamma^2 e^{-\alpha T|m|}$$

Minor adjustments were required in the values for Γ in order to provide agreement between the theoretical models and those resulting from analyzing the data. In addition, the data analysis resulted in values for α which were not previously available. These results are discussed in Section 3.6. However, it should be cautioned that the results obtained on this effort were limited by the data that was available at the time. As more data is made available, the techniques presented in this report should be used to further refine the models.

In the case of discrete multipath, data were not available on the Hazeltine or Texas Instrument types to obtain a time history of the error characteristics. The only time history plots which could be located for discrete multipath errors were compared with the theory and similar results were obtained. These comparisons are discussed in Section 3.7. Time history plots were used to evaluate the discrete multipath error models and favorable comparisons were obtained.

As a result of the work performed on this contract and other recent developments in the MLS program, it is recommended that the following additional study efforts be performed:

- Mathematical models should be developed and validated for the time-reference-scanning beam system which was selected by the MLS committee.

- The developed models should be tested with conventional aircraft landing systems to determine the sensitivity of the autopilot to correlated noise. In addition, any proposed autopilots developed to take advantage of the MLS accuracy should also be tested.
- Optimal onboard detectors can now be developed based upon the spectrum of the noise statistics. Previously, designers could only make assumptions about the characteristics of the noise. However, since more information is now available, realistic designs are possible.
- Error statistics, generated from additional airports, should be subjected to the same analysis. This will determine how sensitive the parameters of the error model are to site variables. At this point, all the software necessary to perform such an analysis has been developed and additional studies can be made quite easily.

2.0

Approach

The MLS system noise can justifiably be considered a stationary random process, and can best be analyzed in a statistical fashion. Ultimately, an autoregressive moving-average model is desired. It has been shown that a model in that form can represent a random process using less components than either an autoregressive or moving-average process. However, estimating the parameters of such a model is complicated. The major effort expended in this contract was directed toward arriving at a best estimate for these parameters based upon the experimental data and comparing them with the assumed parameters of the implemented model. The parameters were thereby verified by using the experimental data.

In the case of a nonstationary random process, as in discrete multipath reflections, a statistical verification of the implemented models via autoregressive moving-average models is ill-advised. The time histories of the error can be compared, however, to determine if the implemented model is reasonable.

The procedure that was followed is outlined below:

- (1) Develop the software to read the data tapes supplied by Texas Instrument and Hazeltine.
- (2) Plot the time histories of the errors in range, azimuth and elevation to determine any obvious problems with the data.
- (3) Develop the software to find the autocorrelation function and smoothed power spectrum. Plot the results for various values of lag, and determine the optimal lag necessary for analysis.
- (4) Develop the software to curve-fit the smoothed power spectrum data with a meromorphic function.
- (5) Determine the best model for the power spectrum and thus specify $|H(j\omega)|^2$.
- (6) From the estimated $|H(j\omega)|^2$ determine the difference equation to model the system noise.

The remaining sections of this report will elaborate upon each of the six areas and present the results of the analysis.

3.0 Discussion

This section will elaborate upon each of the six areas and present the results of the analysis.

3.1 Tape Read Software

The first major effort performed on the contract was directed toward developing computer programs to read the merged magnetic tapes which contained measured data on the Hazeltine and Texas Instruments feasibility hardware versions of the MLS and radar tracking data. These programs as well as the statistical programs were developed on the LRC Kronas Operation System using standard system subroutines. The tape read programs read the tapes and converted the BCD data to the correct floating point value for printing and plotting. The tape read programs are listed in Appendices A and B.

3.2 Time History Plots

Time histories of the measured errors associated with both the Hazeltine and Texas Instruments MLS were plotted and examined to determine whether there were any obvious problems with the data. Resulting plots of these time histories for the Hazeltine and Texas Instrument systems are shown in Figures 2 and 3, respectively. Referring to Figure 2, it is apparent that for the Hazeltine system, both the elevation and azimuth angle data have relatively large spikes which could indicate a system malfunction or other large error sources in the environment. The elevation error spikes are particularly significant because of their large amplitudes. It was felt that the large error spikes should not be attributed to system noise; and thus, it was considered appropriate to remove them (by limiting the maximum error) before the data were analyzed. The altered time history for the elevation data is shown in Figure 4. Although the spikes shown in Figure 4 are considerably smaller than those shown in Figure 2, they are still present and could affect the analysis results.

3.3 Computation of Power-Spectral Density

The next step is to compute the power spectral density. The spectral density of the function $X(t)$, where $X(t)$ is the MLS data, may be defined in the following manner.

Let $X_T(t) = X(t)$ for $-T \leq t \leq T$

and $X_T(t) = 0$ for all other values of t

Let $X_T(j\omega) =$ the Fourier transform of the function $X_T(t)$, which is defined as follows.

$$X_T(j\omega) = \int_{-\infty}^{\infty} X_T(t) e^{-j\omega t} dt \quad (1)$$

$$= \int_{-T}^{T} X(t) e^{-j\omega t} dt \quad (2)$$

The spectral density $S(\omega)$ of the function $X(t)$ is:

$$S(\omega) = \lim_{T \rightarrow \infty} \frac{1}{2T} |X_T(j\omega)|^2 \quad (3)$$

If the signal $X(t)$ is not considered a deterministic function, but merely one member of the ensemble which comprises a random process, the concept of power spectra must be employed to provide a harmonic representation of the function. Strictly speaking, such a representation is valid only when the random process may be said to be both stationary and ergodic. Briefly, this means that the statistics of the process are independent of time (no change in the mechanism of generation is present) and each sample function is representative of the whole ensemble.

It should be noted that if the random process is not stationary, a power spectral representation is invalid and, in fact, no general representation of reasonable utility exists. If only the ergodicity condition is violated, the power spectrum representation can be used.

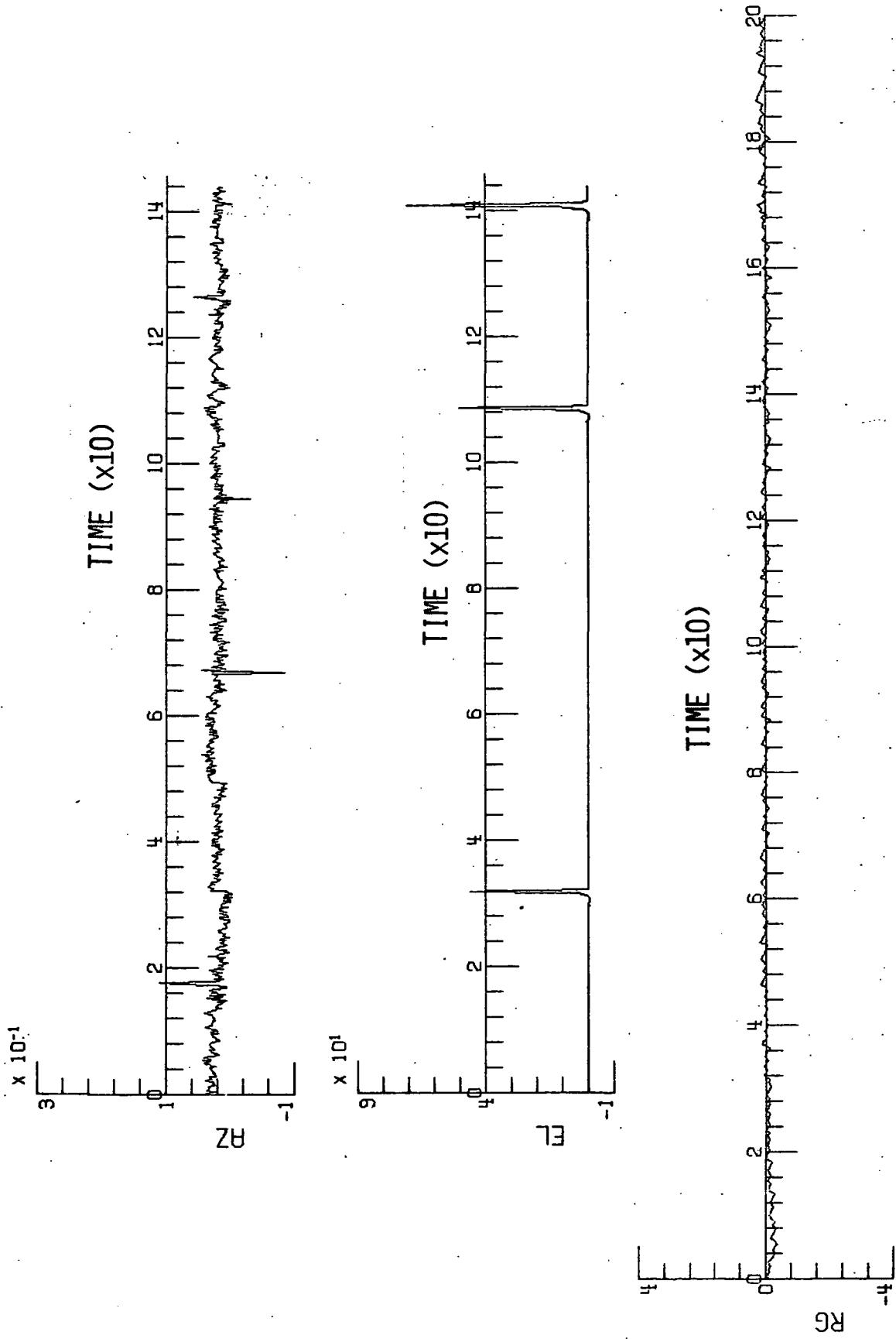


Figure 2. Time History of Errors for Hazeltine Data.

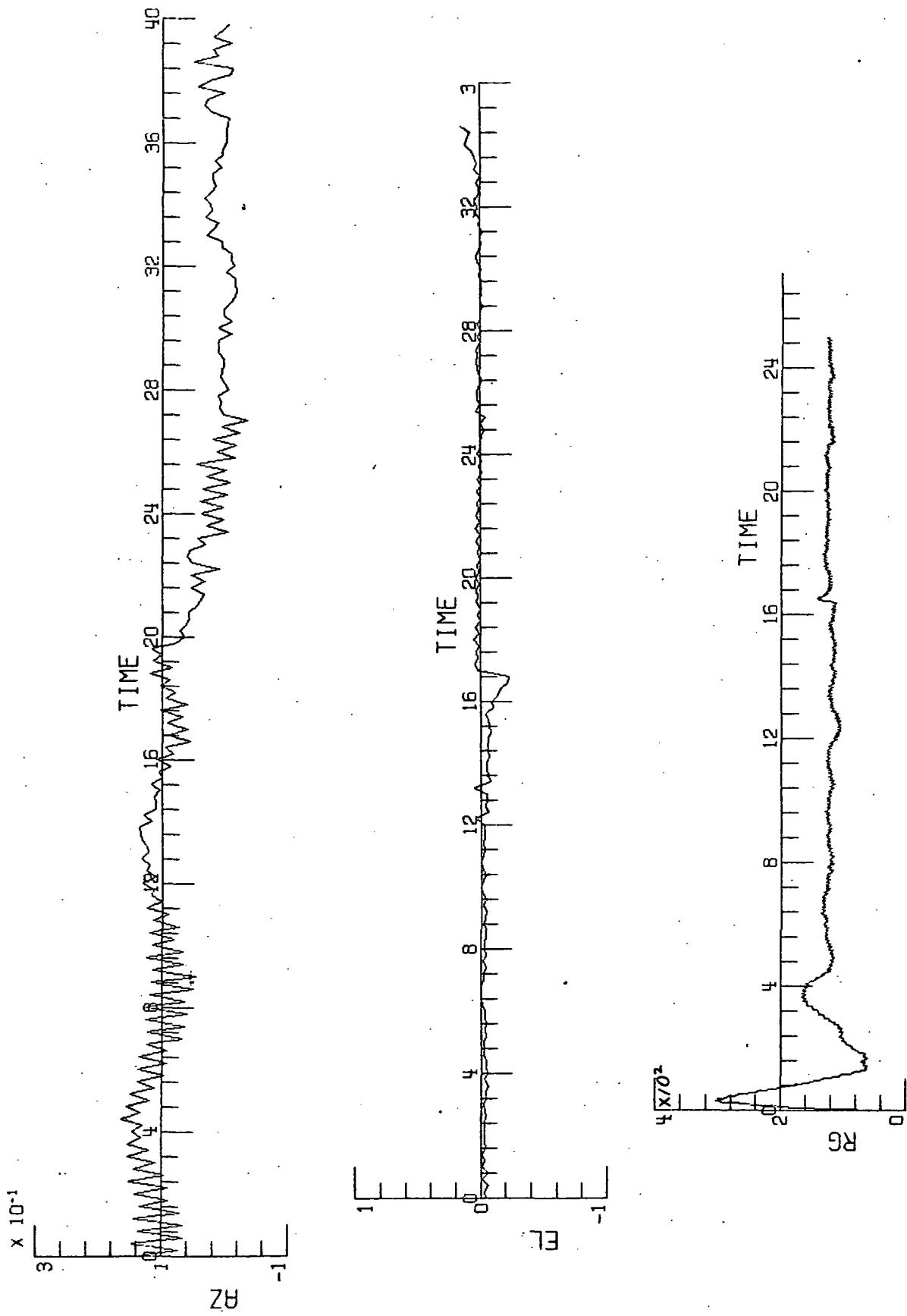


Figure 3. Time History of Errors for Texas Instrument Data.

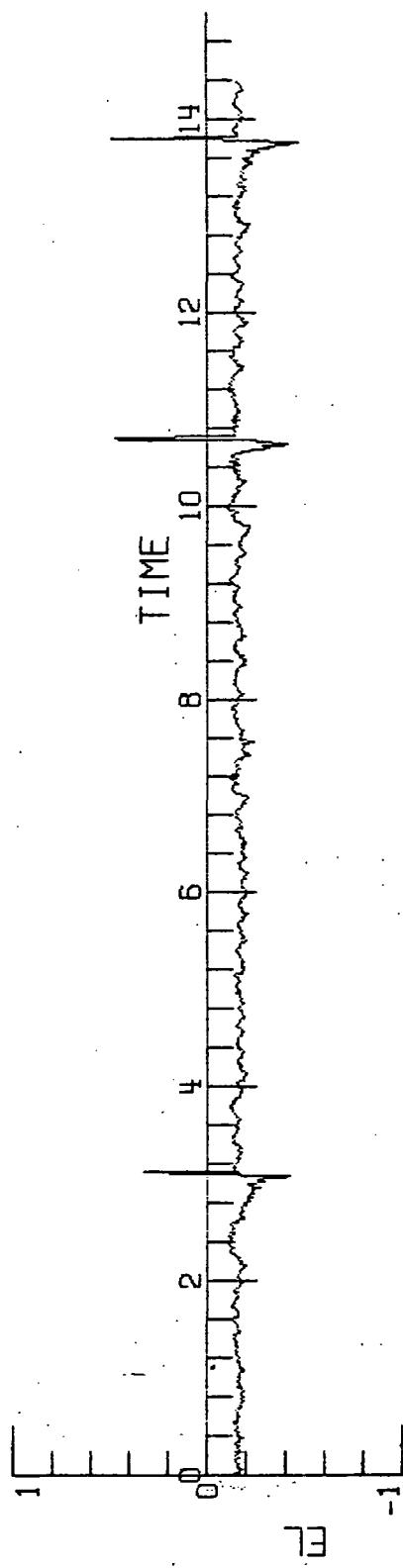


Figure 4. Corrected Time Plot of Hazeltine Data.

A basic limitation of spectral estimation is that data input must always be finite in length. This causes a frequency smearing, or lack of resolution. This can be shown by limiting the data signal, $X(t)$, by using a spectrum window function, $U_{T/2}$, as follows:

$$X_T(j\omega) = \frac{1}{2\pi} \int_{-\infty}^{\infty} U_{T/2}(t) X(t) e^{-j\omega t} dt \quad (4)$$

where $U_{T/2}$ can be defined in several ways; the important point being that

$$\begin{aligned} U_{T/2} &= 0 \text{ for } t > T_{MAX} \& t < -T_{MAX} \\ &= \text{the spectral window otherwise} \end{aligned} \quad (5)$$

From the Fourier frequency convolution theorem, equation (4) may be rewritten as

$$X_T(\omega) = \int_{-\infty}^{\infty} F(\theta) U_{T/2}(\omega - \theta) d\theta \quad (6)$$

where $F(\theta)$ is the true transform and the transform of $U_{T/2}(t)$ is given by

$$U_{T/2}(\omega) = \frac{T}{2\pi} \cdot \frac{\sin(\omega T/2)}{\omega T/2}$$

if $U_{T/2}(t)$ is the boxcar data window. Equation (6) is simply the convolution of two functions in the frequency domain which is equivalent to multiplication of the transformed functions in the time domain (equation 5).

From this it can be seen that $X_T(\omega)$ is the weighted average of the values of $F(\omega)$ about $\omega=\theta$. Also $X_T(\omega)$ is an estimate of $X(\omega)$, the true Fourier transform of $X(t)$. Because of the duality of time domain, multiplication and frequency domain convolution, the finite transform $X_T(\omega)$ at $\omega=\theta$ is an infinite sum of contributions selected from $X(\omega)$ by $U_{T/2}(\omega)$. The magnitude of these contributions is dependent upon the lobes of $U_{T/2}$ on either side of the maximum.

It is thus desirable to minimize the size of the sidelobes of $U_{T/2}$ in order that $X_T(\omega)$ may approximate $X(\omega)$. For larger data samples, ($T \rightarrow \infty$), the approximation improves. In Figure 5, the spectrum windows used in this analysis are shown. The program used to calculate the spectrum generates estimates based upon both windows. All analyses that follow, however, are based upon the smooth spectrum using a Hanning window. The program used to calculate the spectrum estimate is called ASA and is available in the NASA Langley Scientific Library.

Various correlation times or lags in the autocorrelation function were evaluated to determine the number of lags to use in generating the spectral density of MLS error. Figure 6 shows the smoothed spectrum for the elevation data, and Figure 7 the azimuth data, from the Hazeltine tapes. From this it can be seen that choosing too small a lag tends to smooth out many of the variations. For this reason it was decided to use 100 lags for all data. As can be seen with the range and angle data, very little is gained in increasing the lags above 100. At 150 lags the range power spectrum is only slightly more detailed than at 100 lags.

Figures 8 and 9 shows the power spectrum for the Texas Instrument elevation and azimuth data. In this case, increasing the number of lags also has little effect upon the spectrum. It should be emphasized that the Texas Instrument tape had far fewer data points than the Hazeltine tapes. The confidence that one can have in the estimated spectrum decreases as the number of data points decreases. It is not wise, therefore, to attempt to achieve great accuracy with large lags because one is greatly limited by the small amount of data available.

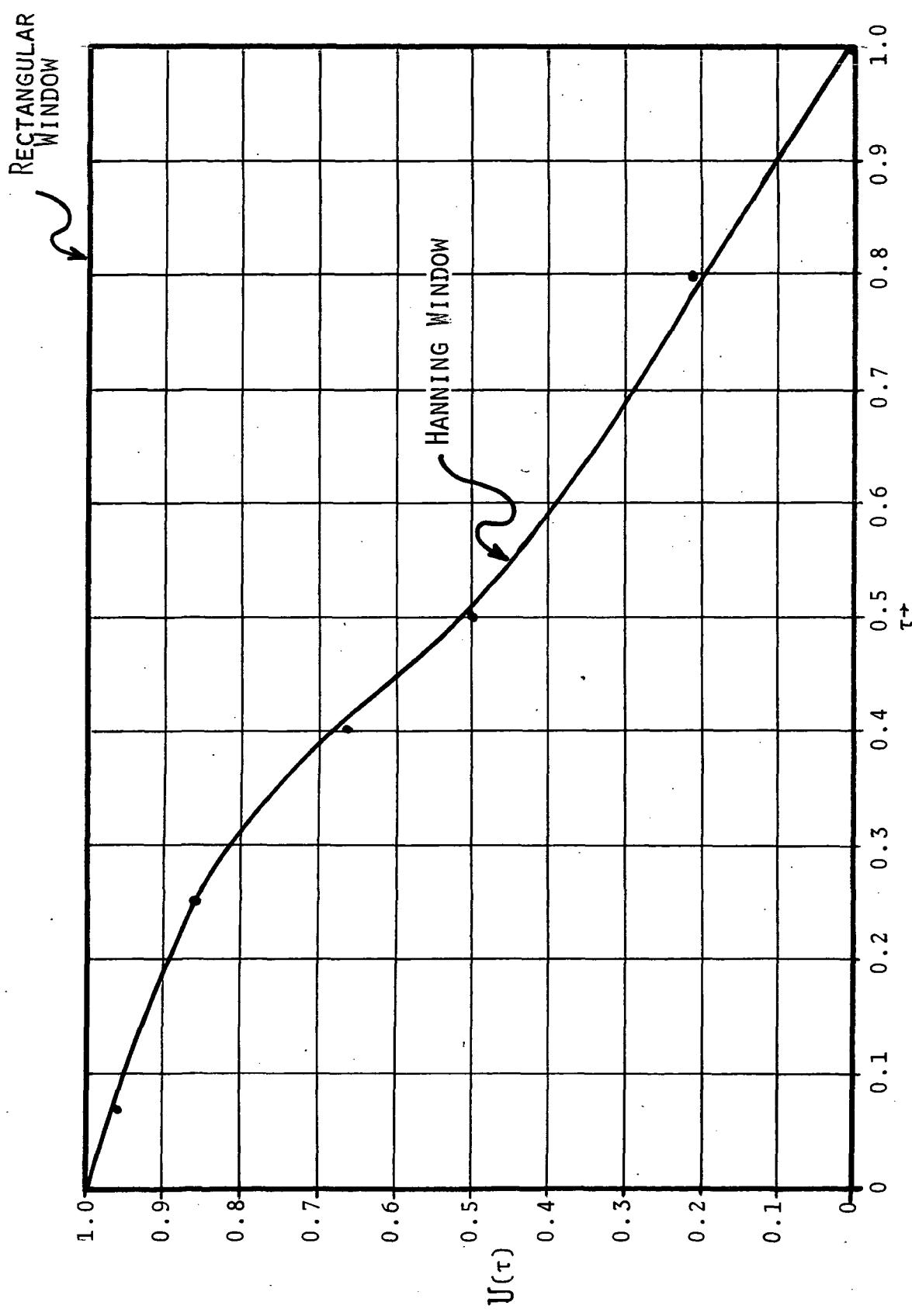


Figure 5. Spectrum Windows Used in Analysis.

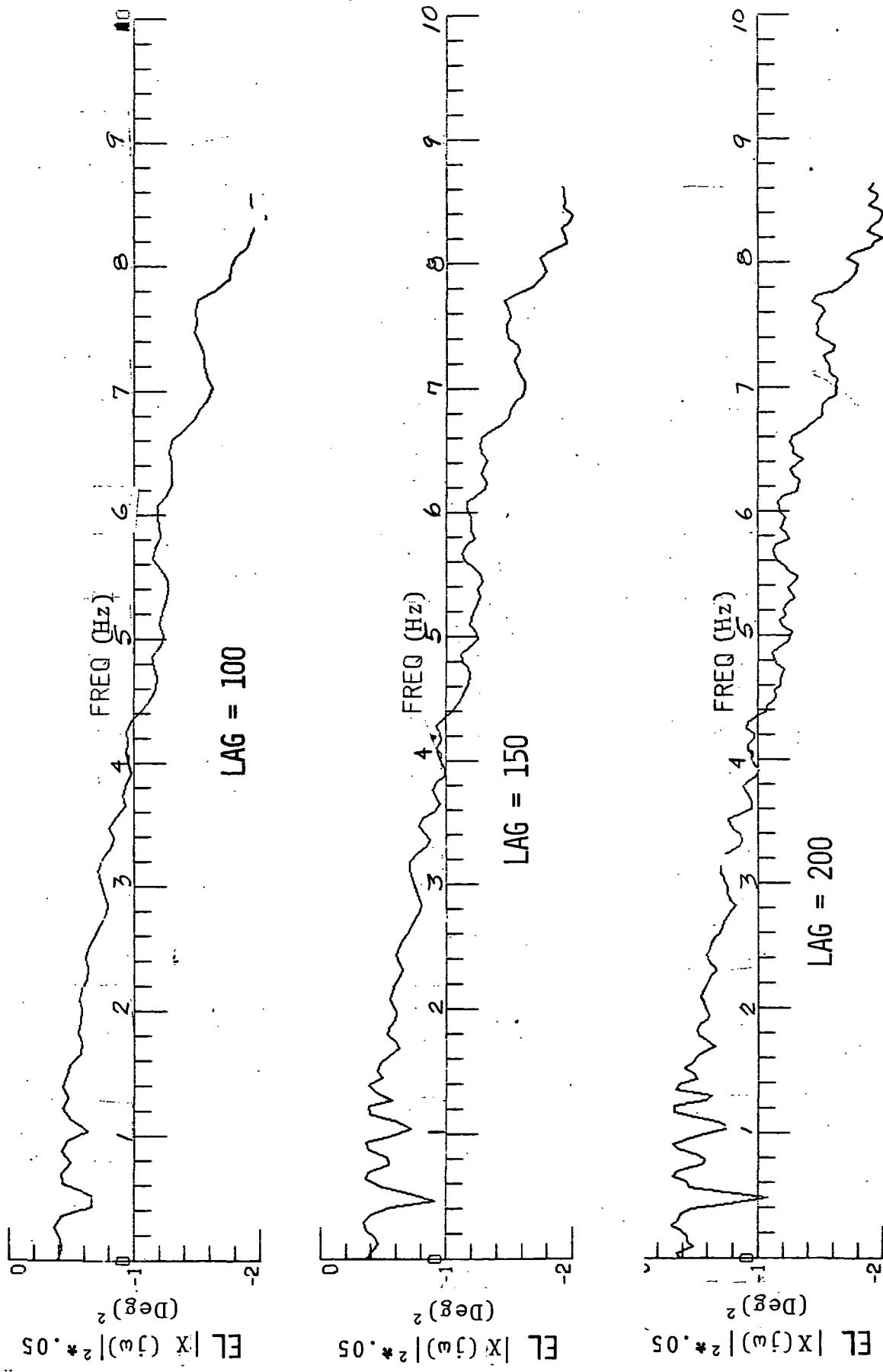


Figure 6. Power Spectrum Density Hazeltine Elevation Error Lag Parameter Plots.

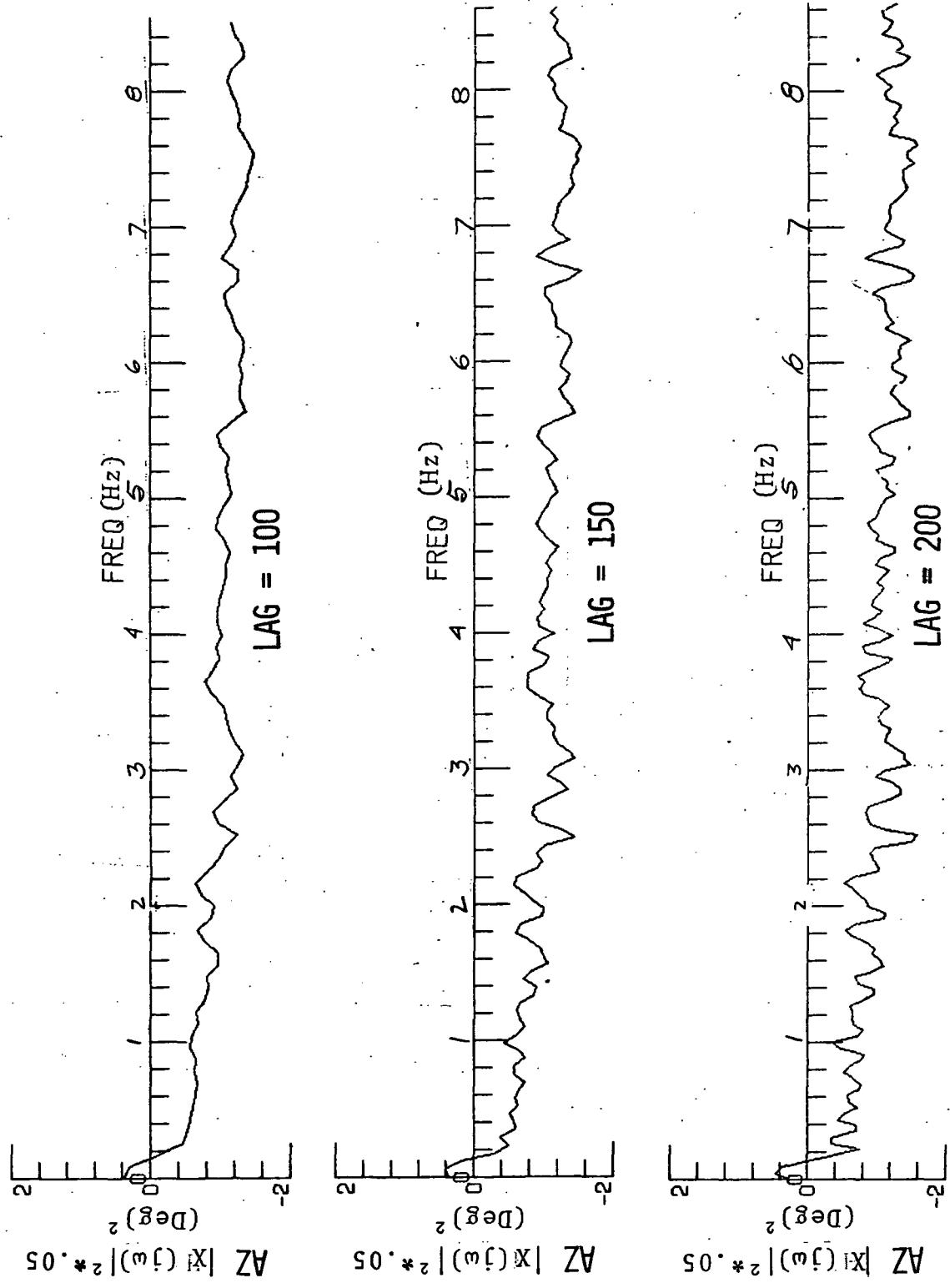


Figure 7. Power Spectrum Density, Hazeltine Azimuth Error Lag Parameter Plots.

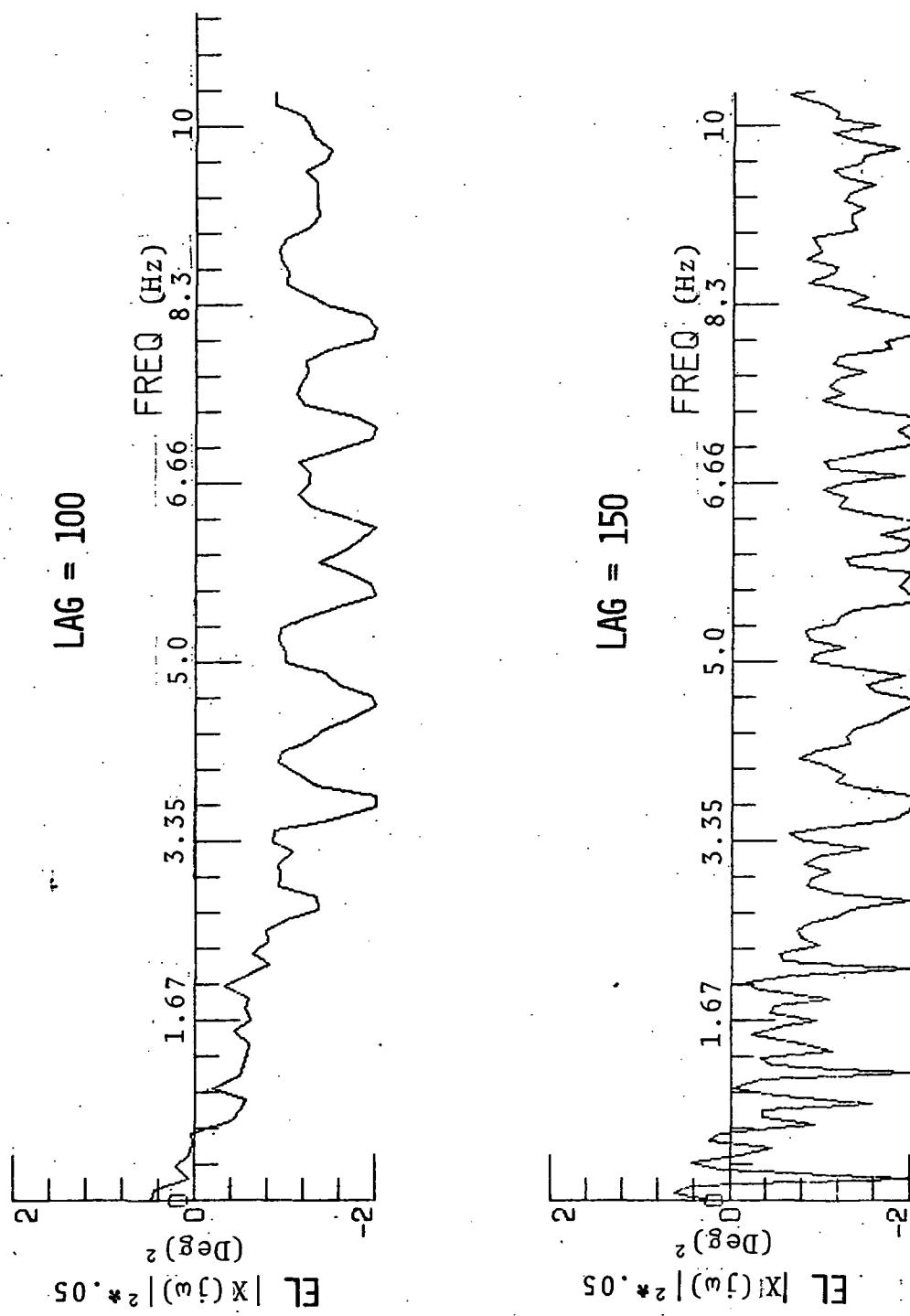


Figure 8. Power Spectrum Desnity Texas Instrument Elevation Error Lag Parameter Plots.

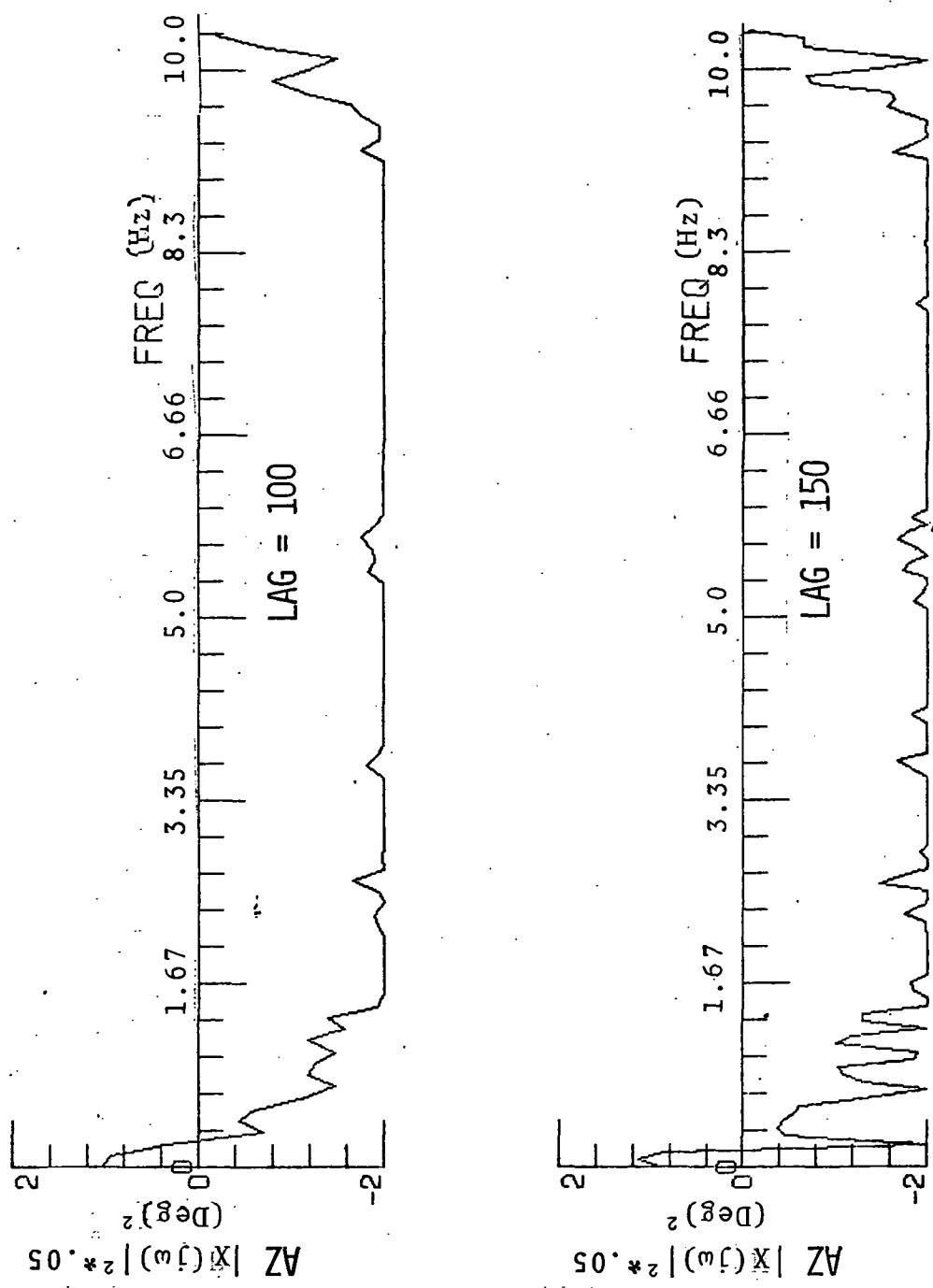


Figure 9. Power Spectrum Density Texas Instrument Azimuth Error Lag Parameter Plots.

3.4 Smoothed Power Spectra

The next step in the analysis is to approximate the spectral density function by meromorphic functions. There are two major reasons for using meromorphic functions.

- (1) The mean-squared error can be calculated if the spectral density of the error is given in the form of a meromorphic function of ω .
- (2) Many methods exist for determining a transfer function which yields a minimum mean-squared error; these methods also are based on the assumption that the spectral density is a meromorphic function of ω .

Therefore, for the application of both of the above mentioned methods, it is necessary first to approximate the spectral density curves by meromorphic functions. In addition to the above applications, the approximation of a given curve by a meromorphic function is of value in solving many problems involved in the synthesis of linear dynamic systems. Therefore, the following methods that are presented have wide application. Since this aspect of the analysis is in some respects the most difficult and at the same time the most important, a brief theoretical background discussion is presented.

Let us assume that we have a given curve $F(\omega)$ and that we wish to approximate it by a rational fractional function $S(\omega)$ in the form

$$S(\omega) = \frac{b_0 + b_1 \omega^2 t + \dots + b_m \omega^{2m}}{a_0 + a_1 \omega^2 t + \dots + a_n \omega^{2n}} \quad (7)$$

We can write

$$0 = (b_0 + b_1 \omega^2 + \dots + b_m \omega^{2m}) - S(\omega)(a_0 + a_1 \omega^2 + \dots + a_n \omega^{2n}) \quad (8)$$

By selecting a number of arbitrary points on the given curve for $(n+m+2)$ particular values of ω and determining the ordinates of the curve, i.e., the values of the function $S(\omega)$ at these points,

we obtain a system of $(n+m+2)$ simultaneous linear equations for $n+m+2$ unknown coefficients $b_0, b_1 \dots b_m; a_0, a_1 \dots a_n$ having the form

$$0 = \left(b_0 + b_1 \omega_1^2 + \dots + b_m \omega_1^{2m} \right) - S(\omega_1) \left(a_0 + a_1 \omega_1^2 + \dots + a_n \omega_1^{2n} \right) \quad (9)$$

$$0 = \left(b_0 + b_1 \omega_{n+m+2}^2 + \dots + b_m \omega_{n+m+2}^{2m} \right) - S(\omega_{n+m+2}) \left(a_0 + a_1 \omega_{n+m+2}^2 + \dots + a_n \omega_{n+m+2}^{2m} \right) \quad (10)$$

The solution of these equations will provide us with the numerical values of the coefficients b_0, b_m, a_0, a_n .

Besides being awkward, this method has the further disadvantage that even if the function $S(\omega)$ is continuous and the number of points taken is very large, it is still impossible to verify that the error (Δ) in the approximation, i.e.,

$$\Delta = F(\omega) - S(\omega) \quad (11)$$

is of sufficiently low absolute value at points which do not coincide with the selected points $\omega_1, \omega_2 \dots$.

An alternate approach to solving this problem is using nonlinear least squares. The standard method for solving least squares problems which lead to nonlinear normal equations depends upon a reduction of the residuals to linear form by first-order Taylor approximations taken about an initial or trial solution for the parameters. The nonlinear nature of the problem can best be seen if $S(\omega)$ is written in the following form:

$$S(\omega; a, b) = \frac{a_0 + a_1 \omega^2 + \dots + a_{n-1} \omega^{2(n-1)}}{b_0 + b_1 \omega^2 + \dots + b_n \omega^{2n}} \quad (12)$$

where the a 's and b 's denote the numerator and denominator coefficients, respectively. The least squares solution to this problem by direct minimization of the approximation error as a function of the filter coefficients requires the solution of a set of nonlinear equations.

Several methods [1-3] are available which have decoupled the solution for the numerator and denominator coefficients. First a linear estimate for the b's is calculated and then the corresponding a's are found. However, these linear estimates are sub-optimal, since the b's are solutions to an overdetermined set of linear equations that minimize the linear equation error $\epsilon(b)$. This $\epsilon(b)$ is a nonlinear mapping of the approximation error $\epsilon(a, b)$. In general, the solution for b that minimizes $||\epsilon(b)||$ is only the same as that which minimizes $||\epsilon(a, b)||$ when $\epsilon(a, b)=0$. Therefore it is necessary to minimize with respect to both a and b.

A program has been used which solves for a and b simultaneously. The method is based on the Marquardt technique [4] which is similar to the Levenberg procedure [5].

$$\text{Let } \phi(B) = \sum_{i=1}^m [W_i^{-\frac{1}{2}} (Y_i - F(X_i, B))]^2 \quad (13)$$

The usual linearized Gauss procedure [6] applied to the problem of minimizing $\phi(B)$ generates estimates by the following procedure:
Start with an initial estimate B.

Solve.

$$A^T A \delta = A^T r \text{ for } \delta. \quad (14)$$

The new estimate is calculated as $B_1 = B + t\delta$ where $0 < t \leq 1$. The process is then repeated at the new estimate B_1 until some acceptable convergence criterion is met. In the above,

$$r_i = \text{the } i\text{th residual} = W_i^{-\frac{1}{2}} [Y_i - F(X_i, B)]$$

A = the matrix defined by

$$A_{ij} = W_i^{-\frac{1}{2}} [\text{partial of } F(X_i, B) \text{ with respect to } b_j]$$

$$\delta = \text{the correction vector, } B_1 = B + t\delta.$$

The Marguardt method differs from the above in that $(A^T A + \lambda I) \delta = A^T r$ is solved instead of $A^T A = A^T r$. The λ value is called a damping coefficient. In practice, the method is implemented in the procedure given below.

Start each iteration with a B_0 and a λ_0 . B_0 is the current estimate of the minimizing parameter vector and λ_0 is an estimate of the "scaled" damping coefficient.

The $A^T A$ and $A^T r$ quantities are formed at the value B_0 . This system is scaled to form $[SA^T AS + \lambda_0 S^2]S^{-1}\delta = SA^T r$. Thus, the λ_0 above is an estimate of the damping constant for this scaled system. Here S is a diagonal matrix with $S_{ii} = [A^T A]_{ii}^{-1/2}$. The scaled correction factor, $S^{-1}\delta$, is computed and the new correction is $B_1 = B_0 + S(S^{-1}\delta)$. If $\Phi(B_1) < \Phi(B_0)$ then a new vector is calculated using $\lambda/10$, this is called B_2 . The new λ estimate is chosen to be the one corresponding to minimize $[\Phi(B_1), \Phi(B_2)]$. The corresponding $B_k; k=1,2$ is taken as the next parameter estimate. If $\Phi(B_1) > \Phi(B_0)$, the new vector, B_2 , corresponding to a damping constant of $\lambda/10$ is still calculated. If $\Phi(B_2) < \Phi(B_0)$, $\lambda/10$ is accepted. If $\Phi(B_2) > \Phi(B_1)$, then λ is increased by factors of 10 until one of two conditions occurs. If some $\lambda * 10^r$ is found that yields an estimate that decreased Φ , this $\lambda * 10^r$ is taken as the damping constant and the new estimate is the B_2 found from $(SA^T AS + \lambda * 10^r S^2)S^{-1}\delta = SA^T r$. However, if the angle between the Marquardt direction vector and the negative gradient direction becomes smaller than 45 degrees before such a $\lambda * 10^r$ is found, then the search on λ is terminated and the direction taken to be examined is the negative gradient.

The entire procedure is repeated until the maximum number of iterations is exceeded or convergence is achieved. Convergence is accepted when $|\delta_i| \leq r + \epsilon |B_i|$ for $i=1, n_0$. Here δ is the correction vector to B and $r \ll \epsilon$.

Since the Marquardt method requires many calculations, a linear least squares method was developed and compared to the Marquardt method.

Let

$$S(\omega) = \frac{a_0 + a_1 \omega^2 + \dots + a_n \omega^{2n}}{1 + b_1 \omega^2 + \dots + b_{n+1} \omega^{2(n+1)}} \quad (15)$$

This can be written as

$$S(\omega) + b_1 S(\omega)\omega^2 + \dots + S(\omega)b_{n+1}\omega^{2(n+1)} = a_0 + a_1\omega^2 + \dots + a_n\omega^{2n}$$

$$S(\omega) = S(\omega)b_1\omega^2 + \dots + S(\omega)b_{n+1}\omega^{2(n+1)} + a_0 + a_1\omega^2 + \dots + a_n\omega^{2n}$$

Making a change of variables as follows:

$$X_1 = \omega^2$$

$$X_2 = \omega^4$$

.

.

.

$$X_n = \omega^{2n}$$

and

$$Y_1 = -S(\omega)\omega^2$$

$$Y_2 = -S(\omega)\omega^4$$

.

.

.

$$Y_m = -S(\omega)\omega^{2m}$$

Results in

$$S(\omega) = b_1 Y_1 + b_2 Y_2 + \dots + b_n Y_n + a_0 + a_1 X_1 + a_2 X_2 + \dots \quad (16)$$

The transformed equation is now linear in its coefficient which implies that the "a's" and "b's" can be estimated by linear regression. The nonlinear correlation between ω and $S(\omega)$ will not affect the efficiency of estimation. In this form, the estimation problem has been greatly simplified. A computer study was made to verify the performance of the linear regression as compared to the nonlinear regression. In general, the linear regression tended to give estimates which weighted all data points equally; whereas,

the nonlinear program tended to weigh more heavily those data points of high magnitude. It is felt that additional work should be done with the linear regression because theoretically it represents a great simplification of the approximation problem. Indeed, it is possible to estimate the coefficients on-line so that one could get a fast estimate of how quickly the error statistics are changing. This method could also be used in designing digital filters where the impulse response is given and the transform $H(Z)$ is desired which will best approximate the impulse response.

3.5 Best Fit Models

The math models which give the best fit to the spectra, based upon the nonlinear regression program are given below; and are illustrated in Figures 10 through 14.

Hazeltine Data:

Elevation

$$|H(j\omega)|^2 = \frac{B_0}{(B_1 + \omega^2)} \quad (17)$$

$$B_0 = 7.024 \quad \text{Standard Error} = 0.4288$$

$$B_1 = 366.37 \quad \text{Standard Error} = 28.02$$

Azimuth

$$|H(j\omega)|^2 = \frac{B_0}{(B_1 + \omega^2)} \quad (18)$$

$$B_0 = 0.1156 \quad \text{Standard Error} = 0.01314$$

$$B_1 = 0.938 \quad \text{Standard Error} = 0.128$$

Range

$$|H(j\omega)|^2 = \frac{B_0}{(B_1 + \omega^2)} \quad (19)$$

$$B_0 = 1.4998 \quad \text{Standard Error} = 2.62$$

$$B_1 = 1.02389 \quad \text{Standard Error} = 0.1092$$

Texas Instrument:

Azimuth

$$|H(j\omega)|^2 = \frac{B_0}{(B_1 + \omega^2)} \quad (20)$$

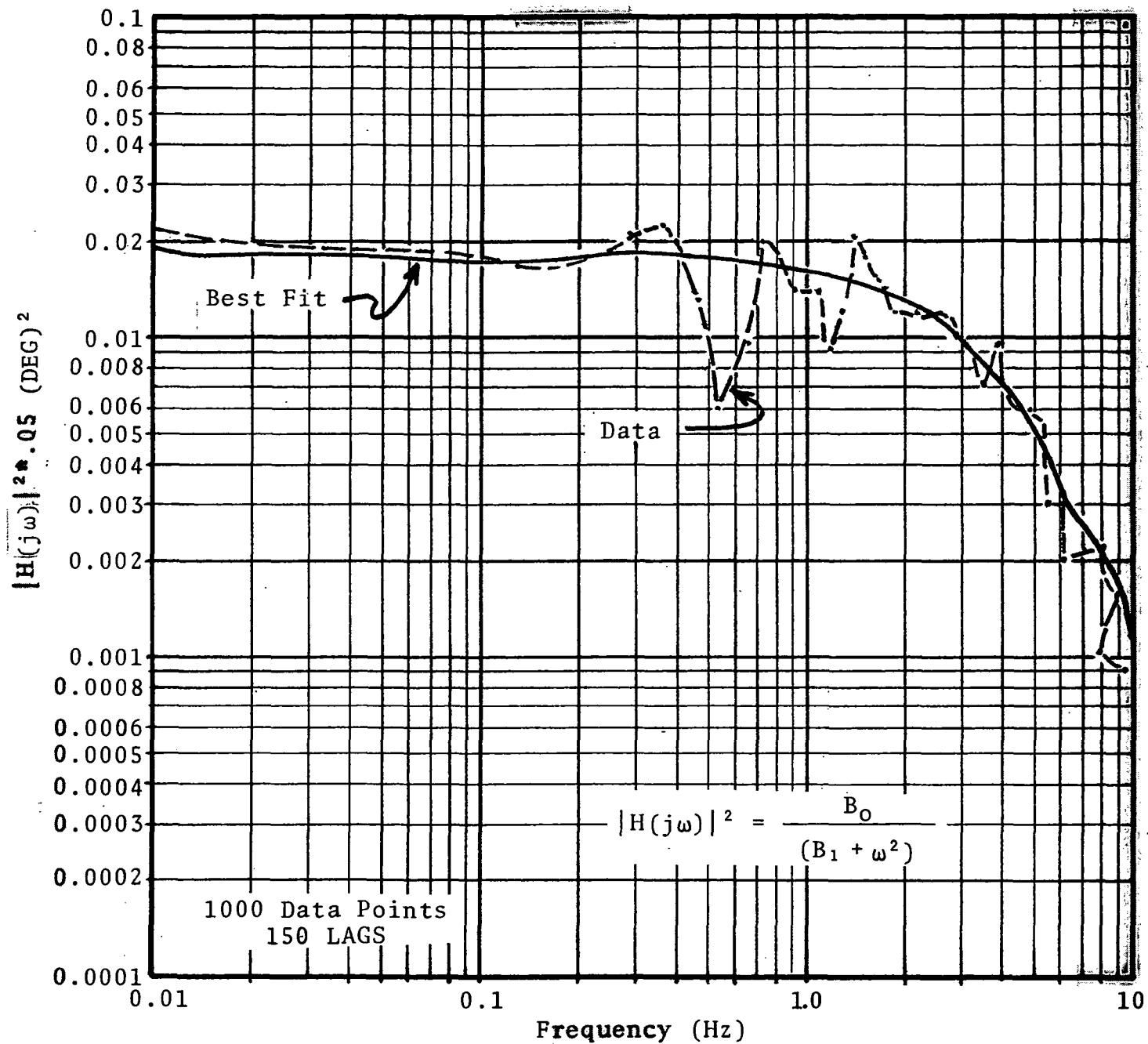


Figure 10. Hazeltine Elevation Data.

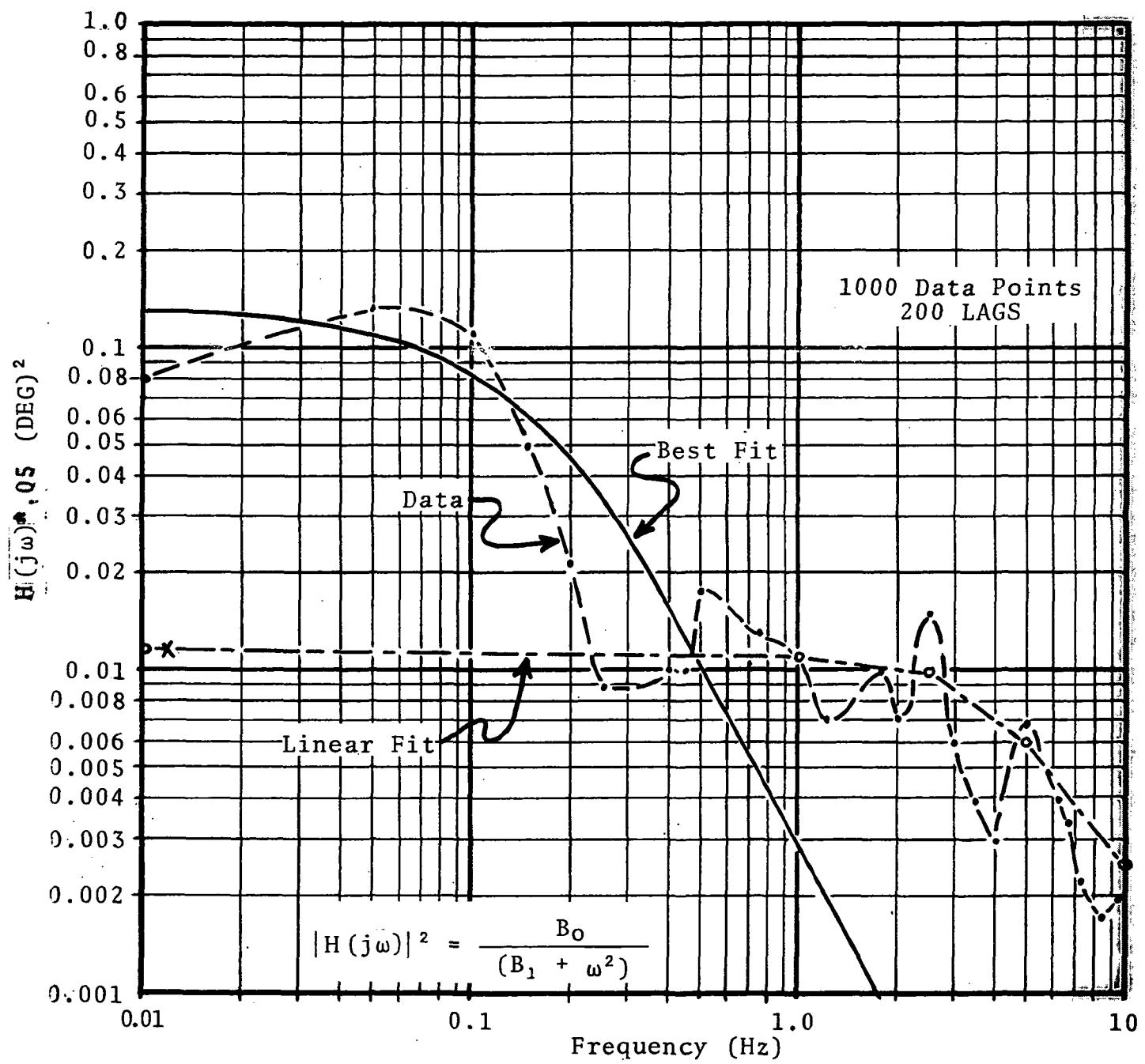


Figure 11. Hazeltine Azimuth Data.

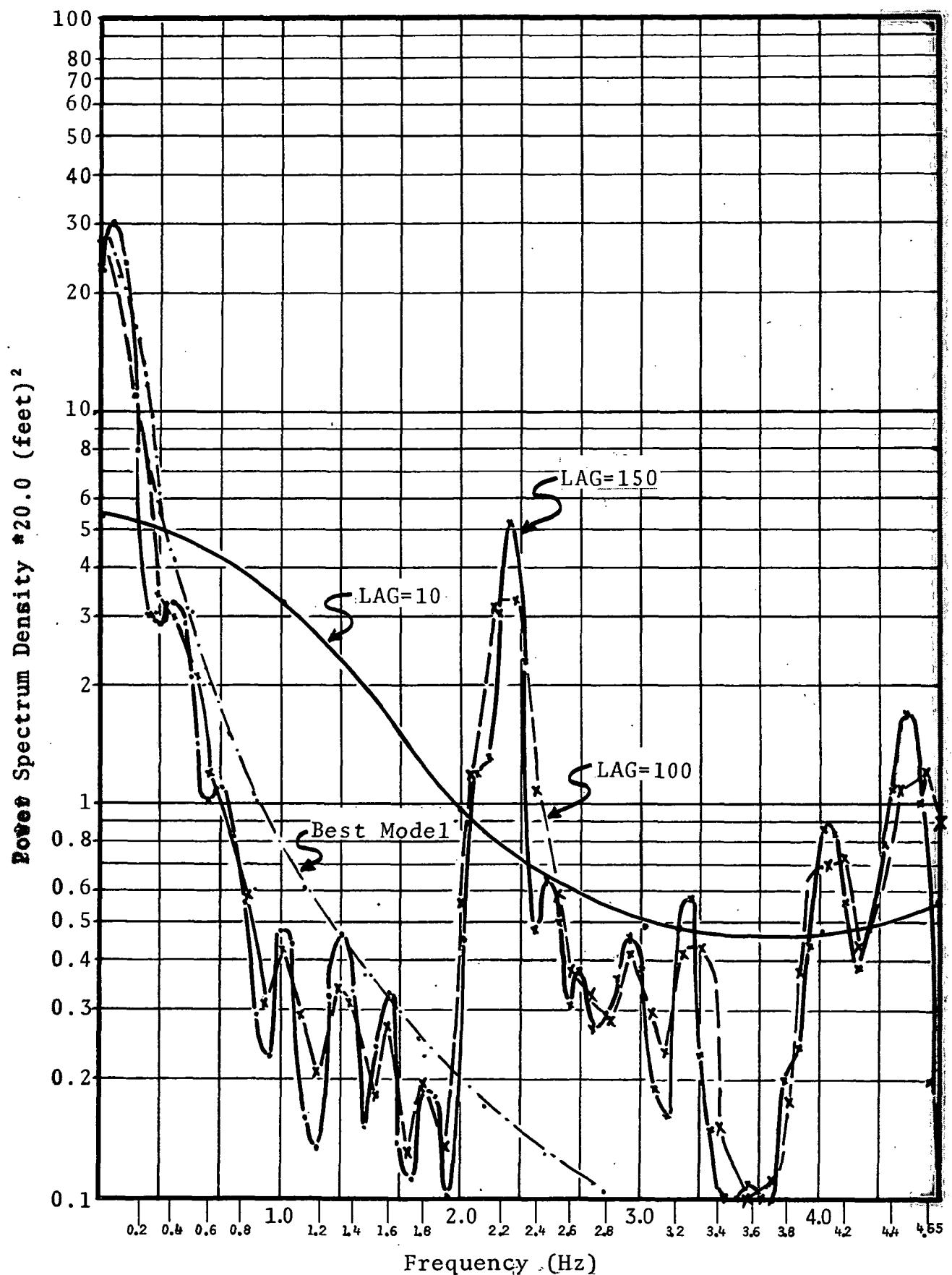


Figure 12. Hazeltine Range, Power Spectrum Density.

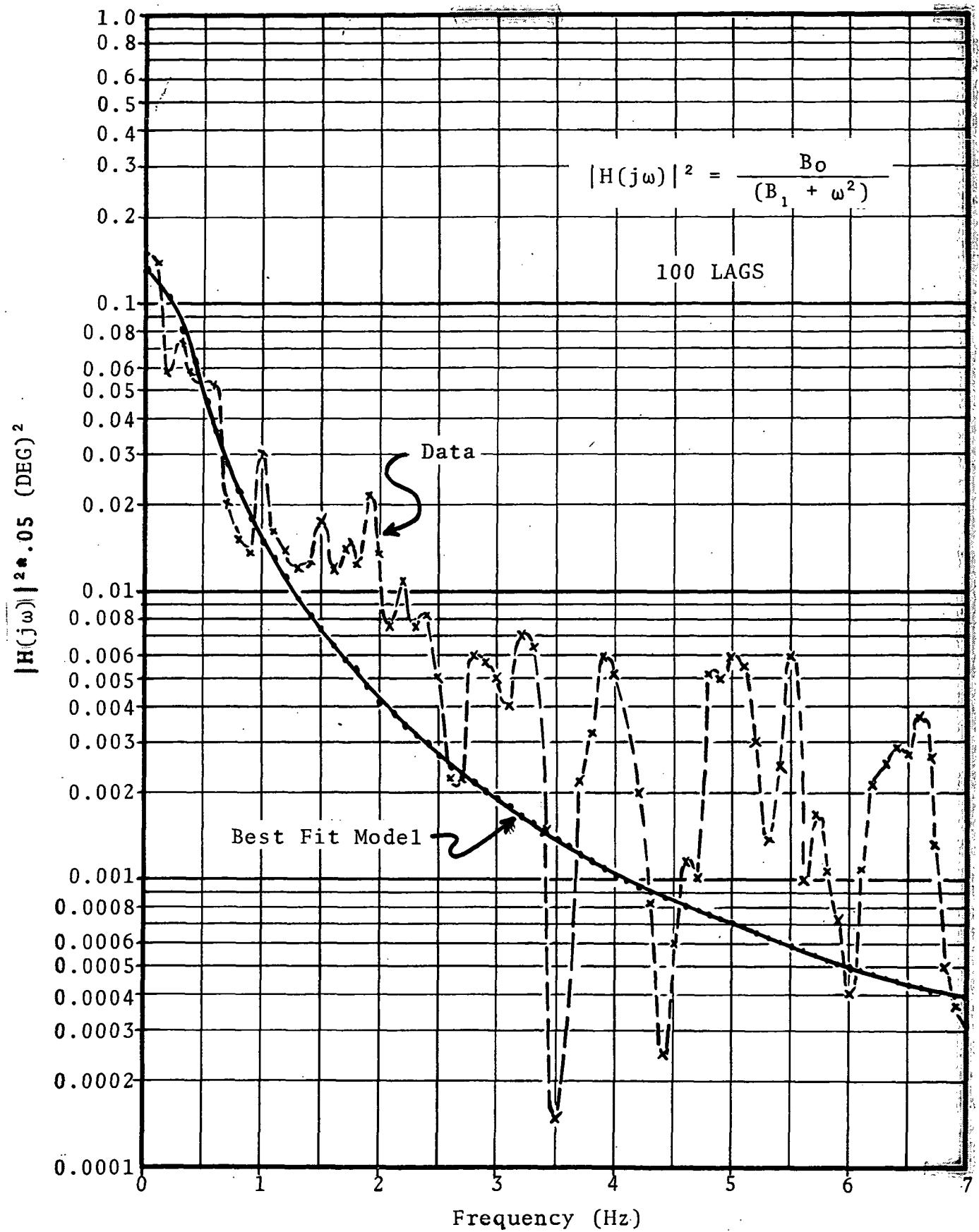


Figure 13. Texas Instrument Elevation Data.

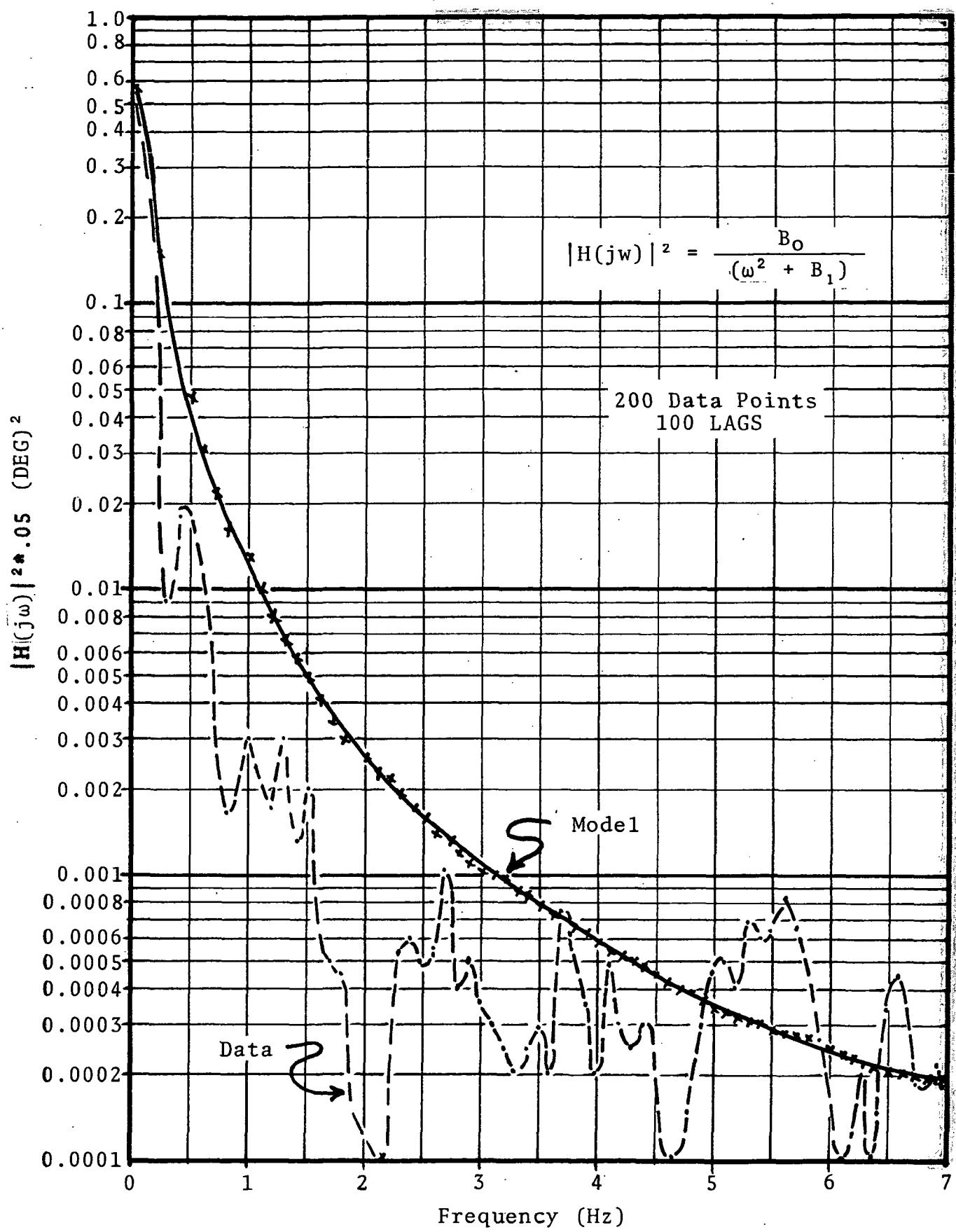


Figure 14. Texas Instrument Azimuth Data.

$$B_0 = 0.33025 \text{ Standard Error} = 0.026$$

$$B_1 = 0.567 \text{ Standard Error} = 0.051$$

Elevation

$$|H(j\omega)|^2 = \frac{B_0}{(B_1 + \omega^2)} \quad (21)$$

$$B_0 = 0.687 \text{ Standard Error} = 0.0634$$

$$B_1 = 5.066 \text{ Standard Error} = 0.5666$$

Several additional models were fit to the data but the results in general were poorer. Table 1 shows a listing of the models with the standard errors of the coefficients. With several models, the coefficients did not converge to a final value; this indicates that the hypothesized model is an inadequate representation of the data. It should also be pointed out that the models that did the best for angle data, for both the Hazeltine and Texas Instrument data, are also the simplest with which to work (no zeros and just a single pole). The specification of the difference equation becomes quite straightforward and the results are more easily understood. For instance, it is possible for the angle data to specify the errors by the correlation time, a variable that is derived simply from the "B" coefficients. This simplicity is a very desirable property, one which cannot be too strongly emphasized.

An important fact to observe from the time plots of the Texas Instrument data (Figure 3) is the small time period of the available data. The plot of the azimuth angle error data indicates that its statistics are not stationary. This is also true for the range data where the first four or five seconds of data are obviously nonstationary. Therefore, a large amount of confidence cannot be placed on the power spectral estimates for the Texas Instrument data. As mentioned earlier, power spectral estimates are not valid for a nonstationary process. In addition, it was extremely difficult finding transfer function coefficients that would represent the data and the number of data points available for angle analysis both for azimuth and elevation data was less than 200. This number is far too small for adequate analysis. For these reasons, it was felt that to carry the Texas Instrument

Table 1. Standard Errors of Coefficients.

HAZELTINE						TEXAS INSTRUMENT					
AZIMUTH			ELEVATION			AZIMUTH			ELEVATION		
	Standard Error			Standard Error			Standard Error			Standard Error	
$B_0 = 0.11040$	00.02606	$B_0 =$	1.3877	2.013	$B_0 =$		$B_0 =$	01.62879	00.2827		
$B_1 = 1.27560$	03.80400	$B_1 =$	12760.0000	21690.000	$B_1 =$		$B_1 =$	03.34141	01.6420		
$B_2 = 1.05183$	56.02000	$B_2 =$	976.4200	17740.000	$B_2 =$		Convergence	$B_2 =$	34.20000	12.4000	
$B_3 = 1.05182$	56.15000	$B_3 =$	976.4170	17750.000	$B_3 =$		Not Possible	$B_3 =$	01.03198	00.3221	
 $ H(j\omega) ^2 = \frac{B_0(B_1 + \omega^2)(B_3 + \omega^2)}{(B_2 + \omega^2)(B_4 + \omega^2)(B_5 + \omega^2)}$											
AZIMUTH			ELEVATION			AZIMUTH			ELEVATION		
	Standard Error			Standard Error			Standard Error			Standard Error	
$B_0 = 00.0894619$	0.002656	$B_0 =$		$B_0 =$			$B_0 =$	/		$B_0 =$	1.63194
$B_1 = .00.2456520$	0.051840	$B_1 =$		$B_1 =$			$B_1 =$			$B_1 =$	3.45148
$B_2 = 00.1410080$	0.122400	$B_2 =$		$B_2 =$		Convergence	$B_2 =$			$B_2 =$	3.45025
$B_3 = -3.5308500$	0.332200	$B_3 =$		$B_3 =$		Not Possible	$B_3 =$			$B_3 =$	34.34100
$B_4 = 14.0772000$	1.028000	$B_4 =$		$B_4 =$			$B_4 =$			$B_4 =$	3.54700
$B_5 = 00.0182540$	0.003520	$B_5 =$		$B_5 =$			$B_5 =$			$B_5 =$	1.03450
 $ H(j\omega) ^2 = \frac{B_0(B_1 + \omega^2)(B_2 + \omega^2)}{(B_3 + \omega^2)(B_4 + \omega^2)(B_5 + \omega^2)}$											

angle data analysis any further would be misleading. Basically, the data does not lend itself to the type of analysis being performed, and to continue with the analysis would be misleading.

The range data, excluding the first five seconds, are also open to question. Unlike the Hazeltine data, there is clearly a bias on the range error data (compare Figures 2 and 3). An attempt was made to continue the analysis with the first five seconds removed from consideration. Even then, however, it must be pointed out that the results obtained may be misleading.

Specification of Different Equations for Digital Simulation

A detailed derivation of the Hazeltine elevation difference equation is given. Since the derivation for the other models is similar, only the results are presented for them.

Hazeltine Elevation:

$$|H(j\omega)|^2 = \frac{B_0}{(B_1 + \omega^2)} \quad B_0 = 7.024 \quad (22)$$

$$B_1 = 366.37$$

$$|H(j\omega)|^2 = \frac{\gamma^2 \alpha}{\alpha^2 + \omega^2} \quad \alpha = 19.1 \quad (23)$$

$$\gamma = 0.184$$

$\Phi(\tau)$ = Autocorrelation function

$\Phi(\tau)$ = Scale Factor e

The scale factor results from the normalization that the subroutine ASA performs. In general $\Phi(\tau)_{\tau=0}$ = mean-squared error

$$\Phi(\tau) \Big|_{\tau=0} = E[X(f)^2] = [E(X)] + \text{Variance} \quad (24)$$

Therefore, in order to properly scale the autocovariance, $E(X)$ and σ^2 must be known. It came to our attention at the conclusion of this project that the subroutine "ASA" which calculates the power spectrum density calculates the following parameter.

$$Z = \frac{X - E[X]}{\sigma}$$

and calculates the spectrum for Z and not X . This in itself is of no major concern as long as $E(X)$ and σ are both known. However, σ is not printed by ASA; in fact, the entire normalization procedure is never mentioned in the documentation.

The normalization procedure does not affect the shape of the spectrum, but it does affect the scale factor. Therefore, all results for the mean-squared error are conservative (i.e., the results do not include the variance which is unknown). Continuing in light of the above, the autocorrelation function is given as follows:

$$\Phi(\tau) = (.184)(.166)^2 e^{-19.1|\tau|}$$

$$\Phi(\tau) = 50.703 \times 10^{-4} e^{-19.1|\tau|}$$

$$\Phi(\tau) = \Gamma^2 e^{-\alpha|\tau|}$$

$$\Gamma = 7.01 \times 10^{-2} \text{ deg}$$

$$\alpha = 19.1 \text{ sec}^{-1}$$

In discrete form,

$$\Phi(m) = \Gamma^2 e^{-\alpha T|m|} \quad (25)$$

The Z transform of $\Phi(m)$ is obtained by taking the sum of the individual Z transforms of the parts for $m > 0$ and $m < 0$. Letting $A = e^{-\alpha T}$ we have

$$\Phi(Z) = \left\{ \frac{1}{1-AZ^{-1}} + \frac{1}{1-AZ} - 1 \right\} \Gamma^2 \quad (26)$$

$$\Phi(Z) = \left\{ \frac{\Gamma \sqrt{1-A^2}}{1-AZ^{-1}} \right\} \left\{ \frac{\Gamma \sqrt{1-A^2}}{1-AZ} \right\} \quad (27)$$

$$H(Z) = \frac{\Gamma \sqrt{1-A^2}}{1-AZ^{-1}} \quad (28)$$

$$H(Z) = \Gamma \sqrt{1-A^2} [1 + AZ^{-1} + A^2 Z^{-2} + \dots] \quad (29)$$

then

$$h(0) = \Gamma (\sqrt{1-A^2}) \quad (30)$$

$$C_{00} = \sqrt{\Phi(0)-h^2(0)} = \Gamma A \quad (31)$$

$$\xi_0 = C_{00}V(0) = \Gamma AV(0) \quad (32)$$

$$y(0) = \Gamma\sqrt{1-A^2} u(0) + \Gamma AV(0) \quad (33)$$

Since $u(0)$ and $v(0)$ are independent and their values do not enter the expression for $y(n)$ for $n \geq 1$, $y(0)$ can be generated more simply from a single random variable having the appropriate variance, by taking

$$y(0) = u(0) \quad (34)$$

Finally for $n \geq 1$

$$y(n) = \Gamma\sqrt{1-A^2} u(n) + Ay(n-1) \quad (35)$$

Since Γ represents the mean-squared error, this variable can be compared to the total error that is specified by RTCA. A copy of this is reproduced in Table 2. As can be seen the Hazeltine system can be used for configuration k, Cat III, based on azimuth data. The remaining results for the Hazeltine data are shown in Table 3.

Several significant conclusions can be made about the results presented in Table 3. First, the correlation time ($\frac{1}{\alpha}$) is considerably different for azimuth and elevation data, varying by a factor of twenty to one. Also, the correlation time for range is similar to the azimuth. The mean-squared error for range is just barely up to the requirements, and in the case of elevation, the requirement has not been met.

Table 2.
RTCA MLS Specifications.

Configuration Operational Use	D Cat. I	F Cat. II	K Cat. III
DME			
Bias	91.4 m (300 ft.) *	30.5 m (100 ft.) *	6.1 m (20 ft.) *
Random			
Total	91.4 m	30.5 m	6.1 m
AZ			
Bias	.125 x degrees	.090 x degrees	.036 x degrees
Random	.065 x degrees	.033 x degrees	.024 x degrees
Total	.141 x degrees	.096 x degrees	.042 x degrees
EL			
Bias	0.050 degrees rads	.050 degrees	.050 degrees
Random	.058 degrees	.035 degrees	.035 degrees
Total	.077 degrees	.061 degrees	.061 degrees

* Random error negligible compared to bias.

Table 3.
Hazeltine MLS Error Models.

Function	Model	A	$\alpha(\frac{1}{sec})$	Γ	$u(n)$
Elevation	$y(n) = \sqrt{\Gamma^2 - A^2} u(n) + Ay(n-1)$	$e^{-\alpha T}$	19.100	7.01×10^{-2} Degrees	IGRS
Azimuth	$y(n) = \sqrt{\Gamma^2 - A^2} u(n) + Ay(n-1)$	$e^{-\alpha T}$	0.971	5.10×10^{-3} Degrees	IGRS
Range	$y(n) = \sqrt{\Gamma^2 - A^2} u(n) + Ay(n-1)$	$e^{-\alpha T}$	1.013	21.1 Feet	IGRS

Note: IGRS = Independent Gaussian Random Sample

Initialization is achieved by setting $y(0) = u(0)$

3.7 Discrete Multipath Errors

The preceding discussion has described the validation results for the system noise component of the MLS error. The other error component included in the MLS model results from discrete multipath reflections. Data were not available on the Hazeltine or Texas Instrument tapes to obtain a time history of the multipath characteristics; however, Reference 8 contains the results of a study of discrete multipath effects. Figure 15 shows this effect for the elevation beam of a time reference MLS. Figure 16 displays the error for the localizer of a frequency reference MLS based on the simulation models described in Reference 9.

As can be seen for both error models the magnitude of the error builds up over a relatively long period of time, reaches a maximum and then decays. This effect can be explained by the model used for the discrete multipath reflections. As the aircraft approaches the specular reflection point the error due to reflections increases. Outside the specular reflection point the error is less but somewhat periodic. It would be highly desirable to develop simulation models for discrete multipath errors for the time reference MLS and to obtain empirical data to better verify this type of performance on both channels.

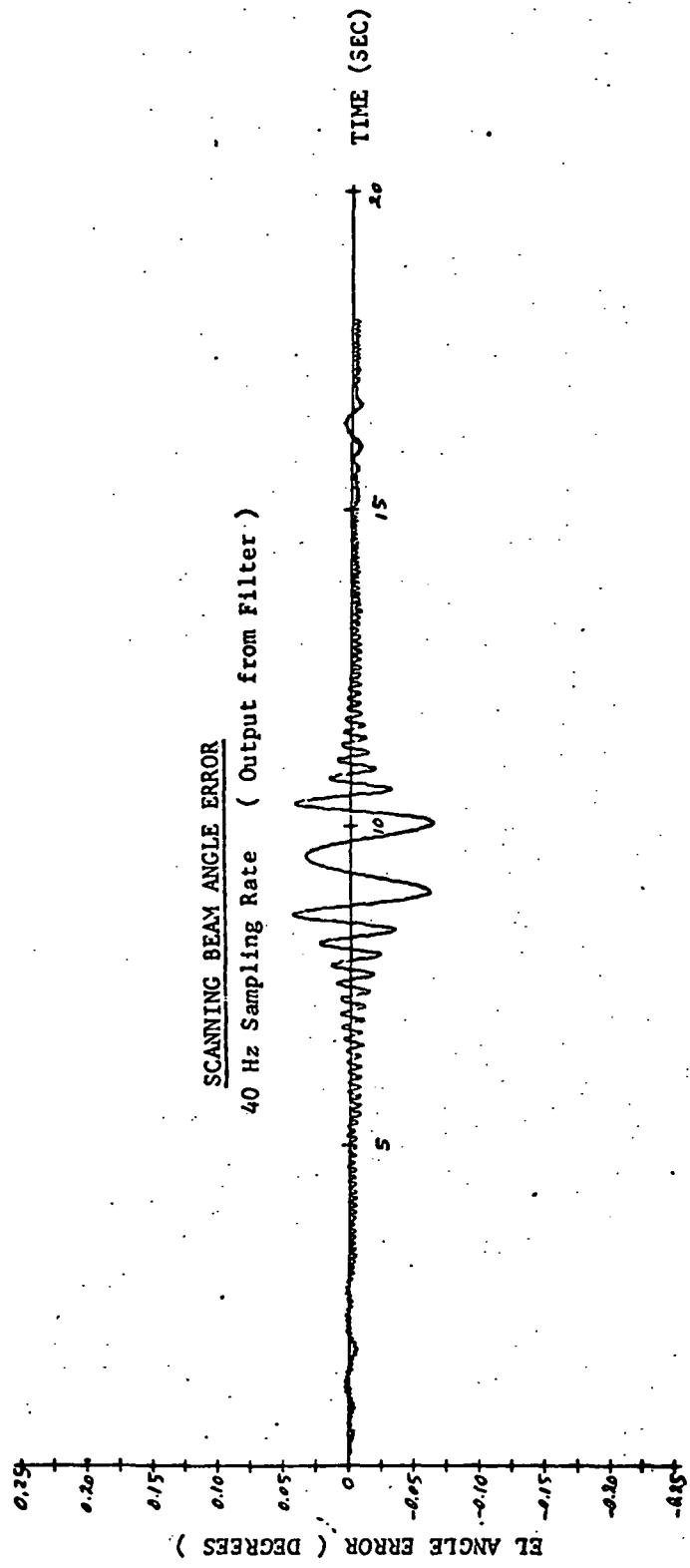


Figure 15. Scanning-Beam Angle Error, 40-Hz Sampling Rate (output from Filter).

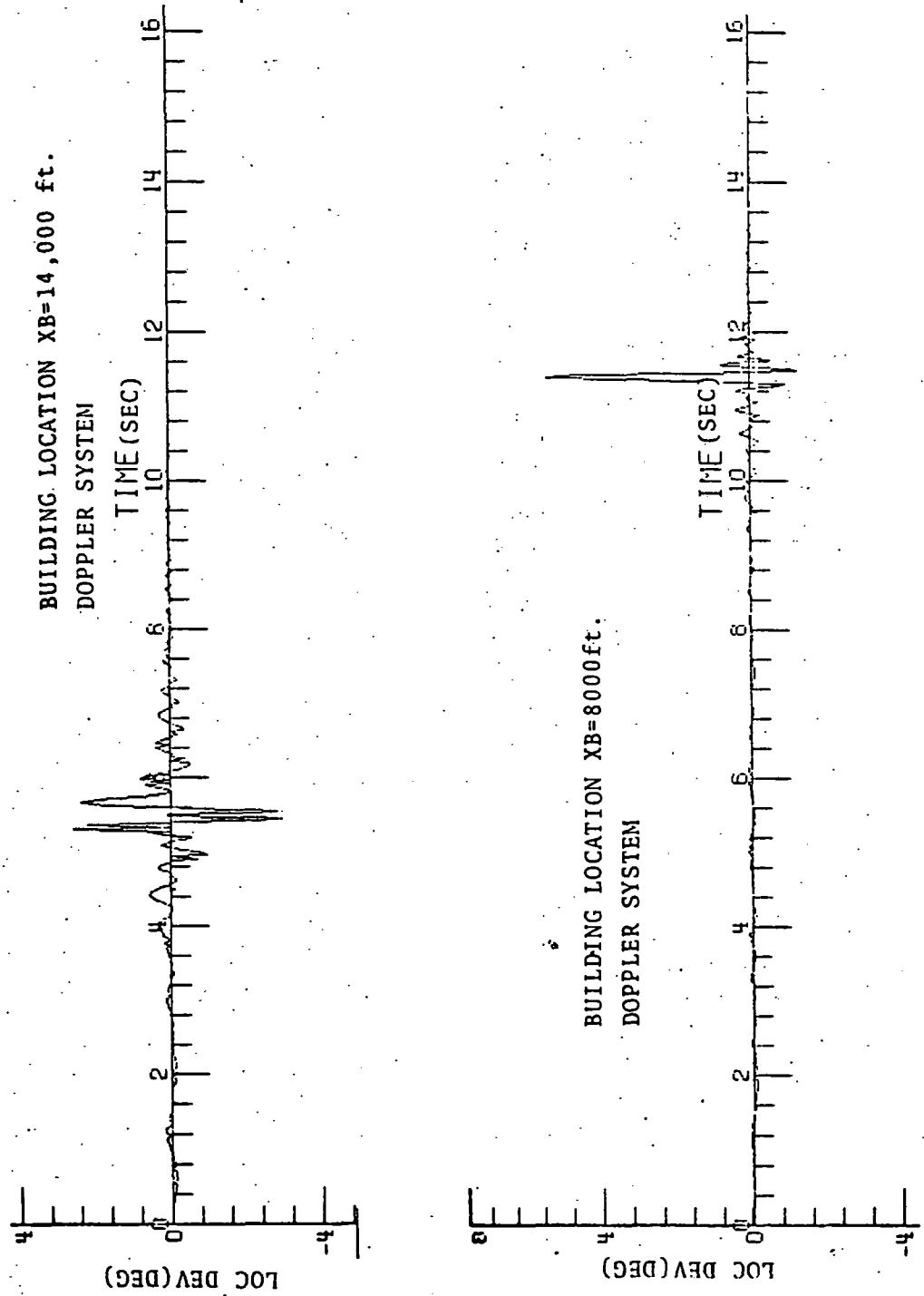


Figure 16. Time Plot of Discrete Multipath Errors.

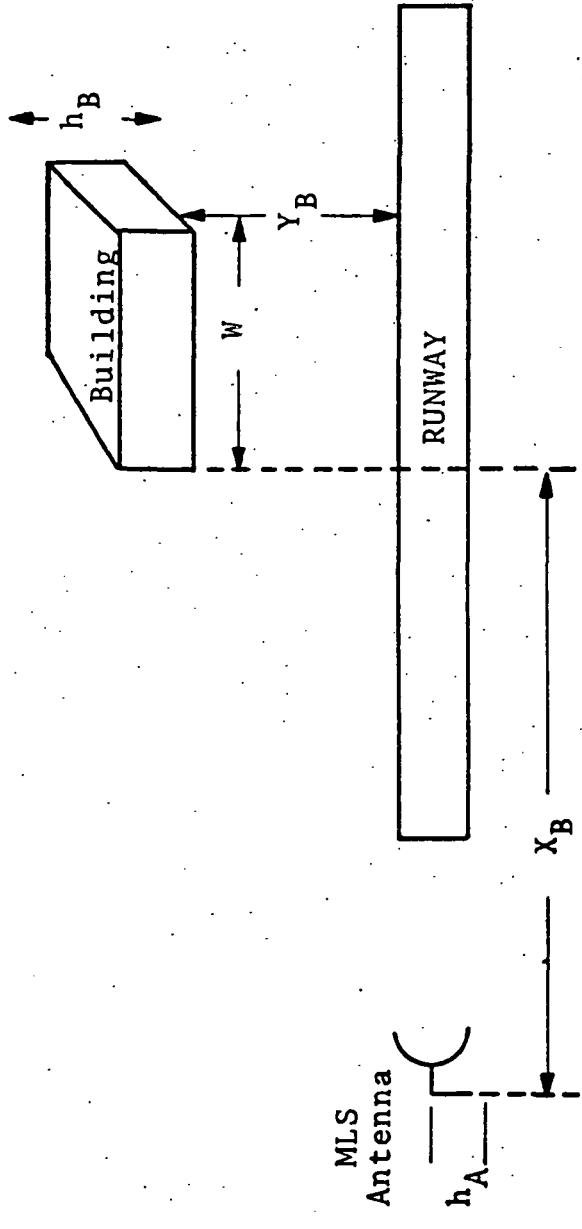


Figure 17. Airport Geometry.

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2. J.L. Shanks, "Recursion Filters for Digital Processing," Geophysics, Volume XXXII, No. 1, pp. 33-51, February 1967.
3. W.C. Yengst, "Approximation to a Specified Time Response," IRE Transactions Circuit Theory, Volume CT-9, pp. 152-162, June 1962.
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5. Levenberg, K. (1944) "A Method for the Solution of Certain Non-Linear Problems in Least Squares," Quarterly Appl. Math., Volume 2, pp. 164.
6. Bard, Y. (1970), "Comparison of Gradient Methods for the Solution of Non-Linear Parameter Estimation Problems," SIAM Journal of Numerical Analysis, Volume 7, No. 1, pp. 157.
7. Anon: "A New Guidance System for Approach and Landing," Volume 2, p. 3 (SC-117 Committee Reports) Radar Technical Commission for Aeronautics, 17.7 H Street, N.W., Washington, D.C., Document DO-148, 18 December 1970.
8. Anon: "Final Report of the MLS Scanning Beam Working Group; MLS Technique Assessment," Logistic Services, LG-340, Washington, D.C.; December 1974, pp. 2-116.
9. NASA CR-132562 "Development and Modification of a Digital Program for Final Approach to Landing."

APPENDIX A
TEXAS INSTRUMENT TAPE READ


```

IF(IFG.EQ.JFG(1))GO TO 10
IF(ABS(DIFR).GT.ABS(PT))GO TO 10
JAZ = JAZ + 1.
MAZ = MAZ + 1.
AZ(JAZ,1) = IH
AZ(JAZ,2) = IM
AZ(JAZ,3) = IS
AZ(JAZ,4) = IMS
AZ(JAZ,1) = PT
AZ(JAZ,2) = MR/100.
AZ(JAZ,3) = MF/100.

C NO FILTERING ON TI
AZ(JAZ,4) = DIFR
AZ(JAZ,5) = DIFR
IAZ(JAZ) = IFG
IF(JAZ.EQ.100)300,10

C          ELEVATION DATA
C
23      CONTINUE
IF(IFG.EQ.JFG(1))GO TO 10
IF(XR.EQ.0 .AND. ZR.EQ.0) GO TO 10
C AVOID 130570
IF(ABS(DIFR).GT.ABS(PT))GO TO 10
JEL = JEL + 1
MEL = MEL + 1
ELT(JEL,1) = IH
ELT(JEL,2) = IM
ELT(JEL,3) = IS
ELT(JEL,4) = IMS
EL(JEL,1) = PT
EL(JEL,2) = MR/100.
EL(JEL,3) = MF/100.
EL(JEL,4) = DIFR
EL(JEL,5) = DIFR
IEL(JEL) = IFG
IF(JEL.EQ.100)300,10

C          RANGE DATA
C
24      CONTINUE

```

```

IF(IXR.EQ.0 .AND. ZR.EQ.0) GO TO 10
IF((JFG.EQ.JFG(1))GO TO 10
      MRNG = MRNG + 1
      RNGT(JRNG,1) = IH
      RNGT(JRNG,2) = IM
      RNGT(JRNG,3) = IS
      RNGT(JRNG,4) = INS
      RANGE(JRNG,1) = PT
      RANGE(JRNG,2) = MR
      RANGE(JRNG,3) = MF
      RANGE(JRNG,4) = DRR
      RANGE(JRNG,5) = DIFR
      RANGE(JRNG,6) = DIFR
      IRNG(JRNG) = IFG
      IF(JRNG.EQ.100)300.10
101 CONTINUE
      ISET = 1
C
C      PRINT DATA
C
      C 300 CONTINUE
      PRINT 900
      900 FORMAT(//5X*K,AZ,DATA*/5X*TIME*11X*AZ(T)*10X*MR*13X*MF*13X*DIFR*
      11X*DIFF*11X*FLAG*10X*RECORD NO.*//)
      DO 500 I=1,JAZ
      WRITE(12) (AZT(I,J),J=1,4),(AZ(I,J),J=1,5)
      DO 500 I=1,JAZ
      WRITE(12) (AZT(I,J),J=1,4),(AZ(I,J),J=1,5),IAZ(I,I)
      500 PRINT 1001,(AZT(I,J),J=1,4),(AZ(I,J),J=1,5),IAZ(I,I)
      1001 FORMAT(2X,I2,*12,*12,*12,*13,S(F10.3,5X),A4,10X,I4)
      PRINT 901
      901 FORMAT(//5X*K EL DATA*/ 6X*TIME*11X*EL(T) *10X*MR*13X*MF*13X*DIFR*
      11X*DIFF*11X*FLAG*10X*RECORD NO.*//)
      DO 501 I=1,JEL
      WRITE(13) (ELT(I,J),J=1,4),(EL(I,J),J=1,5)
      501 PRINT 1001,(ELT(I,J),J=1,4),(EL(I,J),J=1,5),IEL(I,I)
      PRINT 902
      902 FORMAT(//5X*RANGE DATA*/5X*TIME*11X*SRANGE(T)*6X*MR*13X*MF*13X*
      1*RNG RATE*7X*DIFR*11X*DIFF* 6X*FLAG* 4X*REC NO.*//)
      DO 502 I=1,JRNG
      WRITE(11) (RNGT(I,J),J=1,4),(RANGE(I,J),J=1,6)
      DO 502 I=1,JRNG
      WRITE(11) (RNGT(I,J),J=1,4),(RANGE(I,J),J=1,6),IRNG(I,I)
      502 PRINT 1002,(RNGT(I,J),J=1,4),(RANGE(I,J),J=1,6)
      1002 FORMAT(2X,I2,*12,*12,*12,*13,6(F10.3,5X),A4,10X,I4)

```

```

JEL=JAZ=JRNG=0
GO TO 10
      PRINT 1003,MEL,MAZ,MRNG
999   FORMAT//5X*TOTAL EL MEASUREMENTS =*18./5X*TOTAL AZ MEASUREMENTS =
1003 FORMAT//5X*TOTAL EL MEASUREMENTS =*18./5X*TOTAL AZ MEASUREMENTS =
1*18/5X*TOTAL RANGE MEASUREMENTS =*18/
      PRINT 903,IFILE
903   FORMAT//10X*END OF FILE NO. - *13//)
      IFILE = IFILE + 1
      IF(IFILE.EQ.IFT)40,45
40   CONTINUE
      STOP
45   MEL=MAZ=MRNG=0
      ISET = 0
      GO TO 5
      END

```

RITY DETAILS DIAGNOSIS OF PROBLEM

63 CD 19 FIELD WIDTH OF A CONVERSION DESCRIPTOR SHOULD BE AS LARGE AS THE MINIMUM SPECIFIED FOR TH

LIC REFERENCE MAP (R=1)

APPENDIX B
HAZELTINE TAPE READ

```

PROGRAM ASAHAZ(INPUT,OUTPUT,TAPES=INPUT,TAPE7=OUTPUT,TAPE11,
  * TAPE12,TAPE13,TAPE8)
DIMENSION DUM4(4),IDUM4(4)
DIMENSION DUMB(8),DUM3(3),SAVE(1002)
COMMON TC,HEADER,NRFC5,LAG,NLAGS,IFILT,
  * IPRTI,IPRTO,IPLTI,IPLTO,T(10,1002),ERDATA(1002,2),
  * YIN,YIST,YISI,YING,YTO,YTST,YTSI,YTING,
  * XB,CKSUM,TINC,DAXIS(1002),XAXIS(1002),YIN(1002),YTSEL,IPLT
XB=0.
CKSUM=0.
IPLT=1.
YIN=-1.
YIST=-40.
YISI=2.
YING=40.
YT0=-1.
YTST=-50.
YTSI=2.
YTINC=50.
CALL PSFUND
READ(5,*900)HEADER
IF EOF,51 1050,2
CONTINUE
2 FORMAT(A10)
PREAD(5,1002)TC,NRFC5,LAG,TINC,IFILT,IPRTI,IPRTO,IPLTI,IPLTO,ITSEL
WRITE(7,1000)TC,NRFC5,LAG,TINC,IFILT,IPRTI,IPRTO,IPLTI,IPLTO,ITSEL
IF EOF,51 1050,5
CONTINUE
5 NLAGS = LAG + 1
FORMAT(A5,2I5,F5.0,5I1,I2)
990  DO 10 I=1,500
   .. DO 10 J=1,10
10   .. T(J,I)=0.
      FMAX=1./{2.*TINC}
      DFLF=FMAX/LAG
DO 20 I=1,NRECS
20   .. DAXIS(I)=(I-1)*TINC
      .. IF(TC.EQ.2HRC) GO TO 11
      .. IF(TC.EQ.2HAZ) GO TO 12
      .. IF(TC.EQ.2HFL) GO TO 13
      .. WRITE(7,1020)TC
STOP
1020 FORMAT(* TAPE CODE ERROR*,A5)
11   .. DO 21 I=1,NRECS...

```

```

12 NO 22: I=1,NRFC$  

13 READ(12) IDUM4,DUM3,ERDATA(I,1),ERDATA(I,2)  

14 IF(EOF,12 1-16,22)  

15 NRFC$ = I-1  

16 IF(NRFC$.GT.1) GO TO 200  

17 GO TO 1021  

18 CONTINUE  

19 GO TO 200  

20 00 23 I=1,NRFC$  

21 READ(13) IDUM4,DUM3,ERDATA(I,1),ERDATA(I,2)  

22 IF(EOF,13 17,23)  

23 NRFC$ = I-1  

24 IF(NRFC$.GT.1) GO TO 200  

25 GO TO 1021  

26 CONTINUE  

27 CONTINUE  

28 DO 29 I=1,NRFC$  

29 SAVE(I)=ERDATA(I,IFILT)  

30 CALL ASA(NRFC$,LAG,SAVE,XB,TCKSUM)  

31 C T ARRAY IS BACKWARDS  

32 ITSEL=1 TO 10  

33 DO 30 I=1,NLAGS  

34 XAXIS(I) = IT-19 * DELF  

35 X=T(ITSEL,I)*TINC  

36 T(ITSEL,I)=X  

37 IF(X.LT.-.01)X=.01  

38 YIN(I)=ALOG10(X)  

39 WRITE(8)LAG,(T(ITSEL,I),XAXIS(I),I=1,LAG)
40 CALL SPOUT  

41 CALL SPLOT  

42 GO TO 1040  

43 1021 WRITE(7,1030)TC  

44 1030 FORMAT(* EOF,ON*,A5)  

45 1040 REWIND 13  

46 REWIND 12  

47 REWIND 11  

48 GO TO 1

```

1050 WRITE(7,1060)-TC
1060 FORMAT(* ALL INPUT DATA PROCESSED*/*,-
+ * LAST DATA WAS-ONE, A5)
STOP

```
1050 WRITE(7,1060) TC
1060 FORMAT(* ALL INPUT DATA PROCESSED* /,
           * LAST DATA WAS ON*,A5)
      STOP
      END
```

Appendix B. Hazeltine Data. (Continued)

APPENDIX C
NONLINEAR LEAST SQUARES PROGRAM

Note: This program was adapted from
"The Computing Technology Center
Numerical Analysis Library" CTC-39
G.W. Westley, Oct. 1970.

SUBROUTINE NONLSS2(NPAR,NPTS,IN,FAIL,MAXITR,IFXE,NEXT,LINMIN,IE,
110,X,Y,WTS,ATA,B,BDB,EP,LAM,PHI,DAC)

C NONLINEAR LEAST SQUARES ESTIMATOR

C REFERENCES :

C MARQUAARDT "ALGORITHM FOR LEAST-SQUARES ESTIMATION OF NONLINEAR

C PARAMETERS". J.SIAM, VOL. 11,=2 P431

C LEVENBERG "METHOD FOR SOLUTION OF CERTAIN NONLINEAR PROBLEMS IN LS".
C QUART. APPL.MATH.,VOL. 2,P164

000027 REAL ATF(20),ANS(20),ANS1(20),EX(20),NORM,FV,SS,PHI1,PHI2,PHI3,
1 GAM0,TOLR,
000027 REAL X(IE,1),Y(1),B(1),BD(1),WTS(1),EP,DAC,LAM,PHI,ATA(ID,1),
1 FVALUE,PARVAL

000027 INTEGER IFXE(1),INX(20),FAIL

000027 EXTERNAL FVALUE,PARVAL

000027 TOLR = 1.0E-08

000030 GAMAO = 45.

000032 ITER = 0

000033 IR = 20

C DETERMINE THE PARAMETERS TO BE VARIED

C

C

000034 NVAR = 0
000035 DO 10 I=1,NPAR
000036 BDR(I) = B(I)
000042 ANS(I) = 0.0
000043 ANS1(I) = 0.0
000044 IF(IFXE(I).LE.0) GO TO 10
000046 NVAR = NVAR + 1
000047 INX(NVAR) = I
000051 10 CONTINUE
000054 IF(INW.GE.0) WRITE(6,11700) NPAR,NVAR,NPTS,MAXITR,IN,LINMIN,EP,DAC

C EXAMINE THE WTS ARRAY

C NORM = 0.

```

000106      DO 40 I = 1,NPTS
000110      IF (WTS(I)) 20,30,40
000113      20      WTS(I) = 1.0, WTS(I)**2
000117      GO TO 40
000117      30      WTS(I) = 1.0
000122      NORM = NORM + WTS(I)
000122      40      NORM = FLOAT(NPTS)/NORM
000130      NORM = FLOAT(NPTS)/NORM
000131      IF (NORM.EQ.1.) GO TO 60
000133      DO 50 I=1,NPTS
000134      50      WTS(I) = WTS(I)*NORM
C
C   CALCULATE THE INITIAL SUM OF SQUARES
C
000141      60      PHI = 0.0
000142      IF (IW.GT.0) WRITE (6,10208)
000153      DO 70 I=1,NPTS
000155      CALL FVALUE(X,B,IE,FV,I)
000161      SS = Y(I)-FV
000170      IF (IW.GT.0) WRITE (6,10000) I,Y(I),FV,SS
000216      70      PHI = PHI + SS**2*WTS(I)
C
C   START THE DAMPED GAUSSIAN PROCEDURE
C
000226      80      ITER = ITER + 1
000230      IF (IW.GT.0) WRITE (6,11800)
000241      IF (ITER.GT.MAXITR) GO TO 380
000244      DO 90 I=1,NPAR
000245      90      BDB(I) = B(I)
000253      DO 100 I=1,NVAR
000254      ATF(I) = 0.0
000255      DO 100 J=I,NVAR
000257      100     ATAC(I,J) = 0.0
C
C   GENERATE THE ATA AND ATF ARRAYS
C
000273      DO 110 I=1,NPTS
000274      CALL FVALUE(X,B,IE,FV,I)
000300      NORM = WTS(I)*(Y(I)-FV)
000311      CALL PARVAL(X,B,IE,I,EX)
000316      DO 110 L=1,NVAR
000323      J=INXL(L)
000325      ATF(L) = ATF(L) + NORM*EX(J)
000331      DO 110 M=L,NVAR
000332      K = INX(M)
000334      110     ATAL(M)= ATAL(M)+ EX(J)*EX(K) + WTS(I)

```

```
0000356 IF(IW.GT.0) WRITE(6,11500) ITER,PHI,(B(I),I=1,NPAR)
```

```
C PERFORM A LOCAL SCALING ON THE ATA MATRIX TO AID CALCULATIONS
```

```
000407 DO 120 I=1,NVAR
      IF(AT(A(I,I)).EQ.0.) GO TO 410
000411 120 EX(I) = SQRT(AT(A(I,I)))
000416      DO 140 I=1,NVAR
000434          ATF(I) = ATF(I)/EX(I)
000436      DO 140 J=1,NVAR
000440          IF(I.EQ.J) GO TO 130
000442              ATA(I,J) = ATA(I,J)/(EX(I)*EX(J))
000443          GO TO 140
000453      130 ATA(I,I) = 1.0
000461 140 CONTINUE
C DETERMINE A VALID LAMDA FOR THE SCALED PARTIAL MATRIX
C
C
000466 FAC = 1.0
000467 CALL NEWLAM(ATA,LAM,BDB,ATF,ANS,EX,GAMA,FVALUE,PHI1,X,Y,WTS,B,
      > ID,IE,NVAR,NPTS,NPAR,IFAL,INX,IR )
000521      IF(IW.GT.0) WRITE(6,10600) LAM,PHI1,GAMA
000544      IF(IFAL-1) 150,390,400
000547 150  DO 160 I=1,NVAR
000551          KUMMY = INX(I)
000553          IF(ABS(ANS(I)).GT.*TOLR+EP*ABS(B((KDUMLW)))) GO TO 180
000566 160 CONTINUE
000570      IF(PHI.LT.PHI1) GO TO 440
000573 170      DO 170 I=1,NPAR
000574          B(I) = BDB(I)
000602          PHI = PHI1
000603          GO TO 440
000604 180      IF(PHI1.GE.PHI) GO TO 220
000607          IF(LAM.LE.TOLR) GO TO 320
000612          LD0 = LAM*10.0
000614          CALL NEWLAM(ATA,LD0,BDB,ATF,ANS1,EX,GAMA,FVALUE,PHI2,X,Y,WTS,B,
      > ID,IE,NVAR,NPTS,NPAR,IFAL,INX,IR )
000645      IF(IW.GT.0) WRITE(6,10700) LD0,PHI2,GAMA
000670      IF(IFAL-1) 190,390,400
000673 190      IF(PHI2.GE.PHI1) GO TO 320
000676 200      LAM = LD0
000700      DO 210 I=1,NVAR
000702 210      ANS(I) = ANS1(I)
000706          PHI1 = PHI2
000710      GO TO 320
```

```

000710    220 L00 = LAM/10.0
000713      CALL NEWLAM(LATA,LDO,BDB,ATF,ANS1,EX,GAMA,FVALUE,PHI2,X,Y,WTS,B,
> ID,IE,NVAR,NPTS,NPAR,IFAL,INX,IR)
000744      IF (IW.GT.0) WRITE(6,10700) LDO,PHI2,GAMA
000767      IF (IFAL-1) 230,390,400
000772      IF (PHI2.LT.PHI) GO TO 200
000775      L10 = LAM
000777      240 L10 = L10*10.0
001001      CALL NEWLAM(LATA,L10,BDB,ATF,ANS,EX,GAMA,FVALUE,PHI3,X,Y,WTS,B,
> ID,IE,NVAR,NPTS,NPAR,IFAL,INX,IR)
001032      IF (IW.GT.0) WRITE(6,10900) L10,PHI3,GAMA
001055      IF (IFAL-1) 250,390,400
001060      250 IF (PHI3.GE.PHI) GO TO 260
001063      PHI1 = PHI3
001064      LAM = L10
001066      GO TO 320
001067      260 IF (GAMA.GE.GAMA0) GO TO 240
001072      FAC = FAC/2.0
001073      DO 270 I=1,NVAR
001075      270 ANS(I) = ANS(I)/2.0
001101      DO 280 I=1,NVAR
001103      KDUMMY = INX(I)
001105      IF (IABS(ANS(I)).GT.(TOLR+EP*ABSTB(KDUMMY))) GO TO 290
001120      280 CONTINUE
001122      GO TO 430
001122      290 DO 300 I=1,NVAR
001124      KDUMMY = INX(I)
001126      300 BDB(KDUMMY) = B(KDUMMY) + ANS(I)
001135      PHI3 = 0.0
001136      DO 310 I=1,NPTS
001137      CALL FVALUE(X,BDB,IE,FV,I)
001143      310 PHI3 = PHI3 + (Y(I)-FV)**2*WTS(I)
001157      IF (IW.GT.0) WRITE(6,10300) FAC,PHI3
001174      GO TO 250
001175      320 CONTINUE
C
C   AT THE POINT OF THE LINEAR MINIMIZATION PROCEDURE THE CORRECTION
C   VECTOR IS IN ANS AND THE LAMDA THAT PRODUCED THIS VECTOR IS IN
C   LAM.
C
001175      IF (IW.LE.1) GO TO 360
001177      IF (INVAR.EQ.NPAR) GO TO 340
001201      DO 330 I=1,NPAR
001202      330 EX(I) = 0.0
001205      340 DO 350 I=1,NVAR

```

```

001207      K0UMMY = INX(I)
001211      350      EX(KDUMMY) = ANS(I)
001215      WRITE(6,11600) (EX(I),I=1,NPAR)
001234      360      CONTINUE
001234      CALL PARLINANS,B,BDB,FVALUE,PARVAL,X,Y,WTS,PHI,PHII,IE,NPTS,
               > LINMIN,NVAR,INX,DAC,IW,EX)
001266      IF (IW.GT.1) WRITE(6,10800) PHI,(B(I),I=1,NPAR)
001322      DO 370 I=1,NVAR
001324      K0UMMY = INX(I)
001326      IF (ARS(ANS(I)).GT.(TOLR+EP*ABS(BDB(KDUMMY)))) GO TO 80
001341      370      CONTINUE
001343      GO TO 440
001343      380      IF (IW.GE.0) WRITE(6,12300)
001355      FAIL = 2
001356      GO TO 450
001357      390      IF (IW.GE.0) WRITE(6,12000)
001371      FAIL = 3
001372      RETURN
001373      400      IF (IW.GE.0) WRITE(6,11900) GAMA,LAM
001411      FAIL = 4
001412      RETURN
001413      410      IF (IW.GE.0) WRITE(6,11400) I,(B(K),K=1,NPAR)
001443      FAIL = 6
001444      RETURN
001445      420      IF (IW.GE.0) WRITE(6,10500)
001457      FAIL = 5
001460      RETURN
001461      430      IF (IW.GT.0) WRITE(6,12400)
001472      FAIL = 1
001473      GO TO 450
001474      440      IF (ITER.EQ.1) GO TO 80
C
C      THE PROCEDURE HAS CONVERGED
C
001476      FAIL = 0
001477      IF (IW.GE.0) WRITE(6,11802)
001510      IF (IW.GE.0) WRITE(6,12200) ITER
001524      450      IF (IW.GE.0) WRITE(6,12100) PHI,(B(I),I=1,NPAR)
C
C      CALCULATE THE STANDARD ERROR. USE NPTS - NVAR - NEXT AS THE DEF.
C
001554      NORM = SQRT(PHI/FLOAT(NPTS - NVAR - NEXT))
C
C      REMAKE THE PARTIAL MATRIX INSTEAD OF USING THE RE-SCALED MATRIX.

```

C THIS COULD BE EASILY CHANGED.

```
001566      DO 460 I=1,NPAR
001570      460      BOR(I) = 0.0
001574      DO 470 I=1,NVAR
001575      DO 470 J=1,NVAR
001576      470      ATA(I,J) = 0.0
001612      DO 480 I=1,NPTS
001613      CALL PARVAL(X,B,IE,I,EX)
001617      DO 480 L=1,NVAR
001624      J = INX(L)
001626      DO 480 M=L,NVAR
001627      K = INX(M)
001631      480      ATA(L,M) = ATA(L,M) + EX(J)*EX(K)*WT(S(I))
001653      CALL INVRATA(NVAR,ATA,ID,IFU)
001657      IF (IFU.EQ.1) GO TO 420
001665      DO 490 I=1,NVAR
001666      EX(I) = SQRT(ATA(I+1,I))
001702      KDUMMY = INX(I)
001703      490      BD8(KDUMMY) = NORM*EX(I)

C CALCULATE THE CORRELATION MATRIX.
C
001711      DO 500 I=1,NVAR
001712      DO 500 J=1,NVAR
001713      500      ATA(I,J) = ATA(J+1,I)*(EX(I)*EX(J))
001741      IF (IW.LT.0) RETURN
C
C PRINT THE PARAMETERS AND THE STANDARD ERRORS ASSOCIATED TO THEM.
C
001743      DO 555 I=1,NVAR
001745      KDUMMY = INX(I)
001747      WRITE(6,11300) INX(I),B(KDUMMY),BD8
001772      555      CONTINUE
002000      WRITE(6,11802)
002004      IF (NVAR.EQ.1) GO TO 520
002012      IF (FAIL.EQ.2) GO TO 540
C
C PRINT THE CORRELATION MATRIX
C
002014      WRITE(6,11200)
002017      DO 510 I=1,NVAR
002024      510      WRITE(6,11000) I,ATA(J,I),J=1,I
```

```

002055      WRITE(6,11802)
002061      520      WRITE(6,11100)
002065      M = NVAR + 1
002067      DO 530 I=2,M
002074      K=I-1
002076      DO 530 J=1,K
002077      530      WRITE(6,10400) I, AT(I,J)
002132      540      CONTINUE
002132      WRITE(6,11802)
002136      WRITE(6,10100)
002142      DO 550 I=1,NPTS
002147      CALL FVALUE(X,R,IE,FV,I)
002153      SS = Y(I)-FV
002162      550      WRITE(6,10000) I,Y(I),FV,SS
002214      RETURN
002214      10000 FORMAT(1H ,15,3F16.7)
002214      10100 FORMAT(1H0,*FINAL DEVIATIONS*71H ,13X,*CALC*,12X,*0-C*)
002214      10200 FORMAT(1H0,*INITIAL DEVIATIONS*71H ,13X,*OBS*,13X,*CALC*,12X,
002214      > *0-C*)
002214      10300 FORMAT(1H0,*FAC = *,F15.6,6X,* PHI(FAC) = *,F16.7)
002214      10400 FORMAT(1H ,*ROW *,12/(1H ,8E15.6))
002214      10500 FORMAT(1H0,*FINAL A TRANSPOSE A IS NOT POSITIVE DEFINATE*)
002214      10600 FORMAT(1H0,* IN-L = *,F16.8,* PHI(IN-L) = *,F20.10,
002214      > * GAMA = *,F10.4)
002214      10700 FORMAT(1H0,* L/10 = *,F16.8,* PHI(L/10) = *,F20.10,
002214      > * GAMA = *,F10.4)
002214      10800 FORMAT(3H0L ,7F16.7/(3H ,*16X,6F16.7))
002214      10900 FORMAT(1H0,* L*10 = *,F16.8,* PHI(L*10) = *,F20.10,
002214      > * GAMA = *,F10.4)
002214      11000 FORMAT(1H ,*ROW *,12/(1H ,8E15.6))
002214      11100 FORMAT(1H0,* INVERSE MATRIX - LOWER TRIANGULAR PORTION*)
002214      11200 FORMAT(1H0,* CORRELATION MATRIX LOWER TRIANGULAR PORTION ROW BY ROW
002214      > PRINT*)
002214      11300 FORMAT(1H0,* VARIABLE*,6X,*PARAMETER VALUE*,5X,*STANDARD ERROR*)
002214      > (1H ,4X,I2,9X,E15.6,7X,E10.4)
002214      11400 FORMAT(1H0,* THE DIAGONAL ELEMENT RESULTING FROM THE PARTIAL WRT
002214      > B(*,I2,*),IS = 0.0*/1H ,*THE POINT AT WHICH THE FAILURE OCCURRED
002214      > IS */(1H ,7F16.7))
002214      11500 FORMAT(1H0,*ITERATION *,13/1H ,7F16.7/(1H ,16X,6F16.7))
002214      11600 FORMAT(1H0,*DIR-VEC*,5X,6F16.7/(1H0,12X,6F16.7))
002214      11700 FORMAT(1H1,* NPAR#4X*NVAR#4X*NPTS*4X*MAXITR*4X*LINMIN#8X
002214      1*EP*13X*DAC*/1H ,2XI2,6XI2,7XI2,5XI2,5XI2,7XI2,7XE11.4,5XE11.4)
002214      11800 FORMAT(1H0,4(/))
002214      11802 FORMAT(1H0,4(/))

```

002214 11900 FOPNAT(1H0,*GAMA = *,F20.10,* WHEN LAM = *,F20.10/
 > 1H,* THERE PROBABLY EXISTS EXCESSIVELY HIGH CORRELATIONS BETWEEN
 > N THE PARAMETERS*)
002214 12000 FORMAT(1H0,*THE (ATA + LAM*I) MATRIX FAILED TO BE POS. DEF.*)
002214 12100 FORMAT(1H0,7F16.8/1H ,1LX,6F16.8)
002214 12200 FORMAT(1H0,*OPTIMAL POINT REACHED IN *,15,* ITERATIONS*)
002214 12300 FORMAT(1H0,*MAXIMUM NUMBER OF ITERATIONS REACHED - BEST POINT PRIN
 > TED*)/)
002214 12400 FORMAT(1H0,*THE DELTA-B VECTOR REDUCED TO CONVERGENCE LEVEL WHILE
 > GAMA LESS THAN GAMAO.*/1H ,*THE POINT IS PROBABLY OPTIMAL WITHIN
 > ROUNDING ERRORS.*)
002214 END

NONLS2

SUBPROGRAM LENGTH

002762

FUNCTION ASSIGNMENTS

STATEMENT ASSIGNMENTS						
10	-	000051	20	-	000113	30
50	-	000134	60	-	000141	70
90	-	000245	100	-	000257	130
150	-	000547	170	-	000574	180
200	-	000676	210	-	000702	220
240	-	000777	250	-	001060	260
290	-	001122	320	-	001175	330
360	-	001234	380	-	001343	390
410	-	001413	420	-	001445	430
450	-	001524	460	-	001570	470
520	-	002061	540	-	002132	10000
10200	-	002242	10300	-	002252	10400
10600	-	002273	10700	-	002305	10800
11000	-	002336	11100	-	002342	11200
11400	-	002374	11500	-	002414	11600
11800	-	002447	11802	-	002451	11900
12100	-	002503	12200	-	002507	12300

BLOCK NAMES AND LENGTHS

VARIABLE ASSIGNMENTS						
ANS	-	002610	ANS1	-	002634	ATA
B	-	000010	BDB	-	000011	DAC
EX	-	002660	FAC	-	002756	FV
GAMAO	-	002745	GAMO	-	002712	H.
ID	-	000003	IE	-	000002	IFAL
INX	-	002721	IR	-	002747	ITER
K	-	002755	KUMMY	-	002760	L
LDO	-	002714	LINMIN	-	000001	L10
NEXT	-	000000	NORM	-	002704	NYAR
PHI1	-	002707	PHI2	-	002710	PHI3
TOLR	-	002713	WTS	-	000006	X

START OF CONSTANTS
002216

START OF TEMPORARIES

002546

START OF INDIRECTS

002556

UNUSED COMPILER SPACE

032700

```

SUBROUTINE NEWLAM(ATA,LAM,B1,ATF,ANS,GAMA,FVALUE,PHI,X,Y,WTS,
> B, ID, IE, NVAR, NPTS, NPAR, INX, IR)
000030      REAL ATA(ID,1), LAM, B1(1), ATF(IR), ANS(IR), EX(1), GAMA, FVALUE, PHI,
> Y(1), X(IE,1), WTS(1), FV, B(1), SUM1, SUM2, SUM3, COSGAM, CON, DET
000030      INTEGER INX(1)
C

```

```

C      THIS ROUTINE PERFORMS THE FOLLOWING CALCULATIONS:
C

```

```

C      1. SOLVES THE SYSTEM (ATA + LAM*I) * ANS = ATF FOR A GIVEN LAMD
C      2. INCREMENTS THE VECTOR B1 = B + CORRECTION VECTOR.
C      3. COMPUTES PHI FOR THIS NEW VECTOR.
C      4. IFAL = 0 ALL IS OK.
C      5. IFAL = 1 NOT POSITIVE DEFINITE MATRIX
C      6. IFAL = 2 LAMDA - GAMMA TEST FAILURE
C

```

```

000030      CON = 57.2957795
000031      IFAL = 0

```

```

000032      DO 10 I=1, NVAR
000034      ATA(I,I) = 1.0
000041      10   ATA(I,I) = ATA(I,I) + LAM
C

```

```

C      SOLVE THE SYSTEM (ATA + LAM*I) * ANS = ATF
C
000047      CALL SOLVER(ATA,ANS,10,IR,NVAR,1,IFAIL,DET,IOER)
000060      IF (IFAIL.EQ.0) GO TO 20
000065      IFAL = 1
000066      RETURN
C

```

```

C      THIS PORTION PERFORMS THE FOLLOWING CALCULATIONS:
C

```

```

C      1. ADJUST THE ANS ARRAY TO THE FAC COEFFICIENT
C      2. COMPUTE THE COSINE(GAMMA) AND THE TERM GAMMA.
C      REQUIRES THAT THE SYSTEM HAVE AN ARC-COSINE ROUTINE.
C      IF NO SUCH ROUTINE IS PRESENT USE THE FOLLOWING:
C      SS = ABS(COSGAM)
C      GAMMA = CON*(1.5707288+SS*(-.2421144+SS*(.074261-SS*
C      * 0187293)))#SQRT(1.0/SS)
C
C      IF (COSGAM.LT.0.0) GAMMA = 180.0 - GAMMA
C
C      3. PERFORM THE LAMDA-GAMMA TEST FOR FORCED CONVERGENCE.
C

```

```

000067   20 DO 30 I=1,NVAR
000071   30 ANS(I) = ANS(I)/EX(I)
000077   0 IFFAIL = 0
000100   IF INVAR.NE.1 GO TO 40
000102   GAMA = 0.0
000103   GO TO 70
000104   40 SUM1 = 0.0
000105   SUM2 = 0.0
000106   SUM3 = 0.0
000107   DO 50 I=1,NVAR
000110   SUM1 = SUM1 + ANS(I)*ATF(I)
000115   SUM2 = SUM2 + ATF(I)**2
000117   50 SUM3 = SUM3 + ANS(I)**2
000124   COSGAM = SUM1/SQRT(SUM2*SUM3)
000131   GAMA = ACOS(COSGAM) * CON
000134   IF ICOSGAM.GT.0.0 GO TO 60
000142   GAMA = 180.0 - GAMA
000144   IF (GAM.LT.1.0) GO TO 60
000146   IFFAIL = 1
000147   60 IF (IFFAIL.EQ.0) GO TO 70
000150   IFAL = 2
000152   RETURN
000152   70 DO 80 I=1,NVAR
000154   K = INX(I)
000157   80 R1(K) = B(K) + ANS(I)
000166   PHI = 0.0
000167   DO 90 I=1,NPTS
000171   CALL FVALUE(X,B1,IE,FV,I)
000204   90 PHI = PHI + (V(I) - FV)**2 * WTS(I)
000216   RETURN
000216   END

```

NEWLAM
 SUBPROGRAM LENGTH
 000255

FUNCTION ASSIGNMENTS

STATEMENT ASSIGNMENTS

- 20	- 000067	30	- 000071	40	- 000104	60	- 000147
- 70	- 000152						

BLOCK NAMES AND LENGTHS

VARIABLE ASSIGNMENTS

B	- 000006	CON	- 000247	COSGAM	- 000246	DEI	- 000250
FV	- 000242	FVALUE	- 000001	GAMA	- 000000	I	- 000251
ID	- 000007	IDET	- 000253	IE	- 000010	IFAIL	- 000252
IFAL	- 000014	INX	- 000015	IR	- 000016	K	- 000254
NPAR	- 000013	NPTS	- 000012	NVAR	- 000011	PHI	- 000002
SUM1	- 000243	SUM2	- 000244	SUM3	- 000245	WTS	- 000005
X	- 000003	Y	- 000004				

START OF CONSTANTS
 000220

START OF TEMPORARIES
 000225

START OF INDIRECFS
 000236

UNUSED COMPILER SPACE
 041500

```

SUBROUTINE PARLIN(ANS,B,BDB,FVAL,PARVAL,X,Y,WTS,PHI,PHI1,IE,NPTS,
> LINMIN,NVAR,INX,ACC,IW,EX)
REAL ANS(1),B(1),RDB(1),FVAL,PARVAL,X(IE,1),Y(1),WTS(1),PHI,
> PHI1,ACC,FV,EX(1),NORM,CON,R0,F1,L0,L1,F0,R1,L2,F2,R2,R3,R4,DA
INTEGER INX(1)
NLN = 0
DO 10 I=1,NVAR
  BDB(I) = 0.
10   DO 20 I=1,NPTS
    CALL FVALUE(X,B,IF,FV,I)
    NORM = WTS(I)*(Y(I)-FV)
    CALL PARVAL(X,B,IE,I,EX)
    DO 20 L=1,NVAR
      KDUMMY = INX(L)
      BDB(L) = BDB(L) + NORM*EX(KDUMMY)
20   DO 30 I=1,NVAR
      NORM = NORM + ANS(I)*BDB(I)
30   CON = NORM
      NORM = ABS(PHI/NORM)
      RD = AMIN(NORM,1.0)
      IF (RD.EQ.1.0) GO TO 60
      DO 40 I=1,NVAR
        KDUMMY = INX(I)
        BDB(KDUMMY) = B(KDUMMY) + R0*ANS(I)
40   DO 50 I=1,NPTS
      CALL FVALUE(X,BDB,IE,FV,I)
      F1 = F1 + (Y(I)-FV)**2*WTS(I)
50   IF (IW.GT.2) WRITE(6,10100) F1,RD
      NLN = NLN + 1
      GO TO 70
10000201   60 F1 = PHI
10000203   70 L0 = 0.0
10000204   70 L1 = RD
10000206   80 F0 = PHI
10000207   80 R1 = CON*R0*RO*F1-F0+2.0*CON*RO
10000216   90 IF (R1.GT.0.0) GO TO 130
10000220   90 L2 = L1 + L1
10000222   100 F2 = 0.0
10000223   100 DO 110 I=1,NVAR
      KDUMMY = INX(I)
10000225   110 BDB(KDUMMY) = B(KDUMMY) + L2*ANS(I)
10000230   110 DO 120 I=1,NPTS

```

```

000244      CALL FVALUE(X,BDB,IE,FV,I)
000245      120      F2 = F2 + (Y(I)-FV)**2*WTS(I)
000246      IF (IW.GT.2) WRITE(6,10100) F2,L2
000247      NLN = NLN + 1
000301      IF (NLN.GT.LINMIN) GO TO 320
000304      IF (F2.GE.F1) GO TO 200
000306      L0 = L1
000310      F0 = F1
000311      L1 = L2
000312      F1 = F2
000312      GO TO 90
000313      130 IF (R1-L1) 150,90,140
000316      140 L2 = R1
000320      GO TO 100
000320      150 R2 = AMAX1(.25*R0,AMIN1(.75*R0,R1) )
000330      DO 160 I=1,NVAR
000332      KDUMMY = INX(I)
000335      160 BDB(KDUMMY) = B(KDUMMY) + R2*ANS(I)
000345      NORM = 0.0
000346      DO 170 I=1,NPTS
000347      CALL FVALUE(X,BDB,IE,FV,I)
000352      170  NORM = NORM + (Y(I)-FV)**2*WTS(I)
000367      IF (IW.GT.2) WRITE(6,10100) NORM,R2
000405      NLN = NLN + 1
000407      IF (NLN.GT.LINMIN) GO TO 320
000412      IF (NORM.LT.F0) GO TO 180
000414      L1 = R2
000416      F1 = NORM
000417      R0 = R2
000420      GO TO 80
000420      180 IF (NORM.LE.F1) GO TO 190
000423      L0 = R2
000424      F0 = NORM
000425      GO TO 90
000425      190 L2 = L1
000427      F2 = F1
000430      L1 = R2
000431      F1 = NORM
000432      200 K = 1
000433      R3 = .5*(F0*(L1**2-L2**2) + F1*(L2**2-L0**2) + F2*(L0**2-L1**2))/
000433      > (F0*(L1-L2) + F1*(L2-L0) + F2*(L0-L1))
000465      IF (ABS(R3-L1).LE.ACCL1) GO TO 290
000472      R4 = AMAX1(L0+1*(L2-L0),AMIN1(L0+9*(L2-L0),R3))
000506      210 NORM = 0.0
000507      DO 220 I=1,NVAR

```

```

000511      KSUMMY = INX(I)
000514      220      80B(KSUMMY) = B(KSUMMY) + R4*ANS(I)
000524      DO 230 I=1,NPTS
000525      CALL FVALUE(X,BDB,IE,FV,I)
000530      230      NORM = NORM + (Y(I)-FV)**2*WTST(I)
000545      IF (IW.GT.2) WRITE(6,10000) NORM,R4
000563      NLN = NLN# 1
000565      IF (NLN.GT.LINMIN) GO TO 320
000570      IF (R4 .EQ. L1) GO TO 290
000572      IF (R4 .GT. L1) GO TO 270
000575      IF (NORM.LT.F1) GO TO 250
000577      L0 = R4
000600      F0 = NORM
000601      IF (K.EQ.2) GO TO 200
000603      R4 = (L1 + L2)/2.0
000606      240 K = 2
000607      GO TO 210
000610      250 L2 = L1
000612      F2 = F1
000613      260 L1 = R4
000615      F1 = NORM
000616      GO TO 200
000617      270 IF (NORM.GE.F1) GO TO 280
000622      L0 = L1
000623      F0 = F1
000624      GO TO 260
000624      280 L2 = R4
000626      F2 = NORM
000627      IF (K.EQ.2) GO TO 200
000631      R4 = (L1 + L2)/2.0
000634      GO TO 240
000635      290 DA = -1.0
000637      PHI = PHI1
000641      IF (PHI1.LE.F1) GO TO 300
000643      DA = L1
000644      PHI = F1
000645      300 DO 310 I=1,NVAR
000647      K = INX(I)
000652      BUB(K) = BIK
000655      ANS(I) = DA*ANS(I)
000657      310 BCK) = BIK + ANS(I)
000665      GO TO 330
000665      320 DA = 1
000667      PHI = PHI1
000671      CON = AMINI(F0,FI,F2)

```

```
000676 IF (CON.GE.PHI1) GO TO 300
000700   IF (CON.EQ.F0) DA = L0
000703   IF (CON.EQ.F1) DA = L1
000707   IF (CON.EQ.F2) DA = L2
000713 PHI = CON
000715   GO TO 300
000715   330 RETURN
000716   10000 FORMAT (3H0B ,F25.12,5X,F15.6)
000716   10100 FORMAT (3H0S ,F25.12,5X,F15.6)
000716   END
```

PARLIN

SUBPROGRAM LENGTH
001033

FUNCTION ASSIGNMENTS

STATEMENT ASSIGNMENTS

- 10	- 000027	30	- 000104	60	- 000201	70	- 000203
- 80	- 000207	90	- 000220	100	- 000222	130	- 000313
- 140	- 000316	150	- 000320	180	- 000420	190	- 000425
- 200	- 000432	210	- 000506	240	- 000606	250	- 000610
- 260	- 000613	270	- 000617	280	- 000624	290	- 000635
- 300	- 000645	320	- 000665	330	- 000715	10000	- 000732
- 10100	- 000736						

BLOCK NAMES AND LENGTHS

VARIABLE ASSIGNMENTS

- ACC	- 000011	CON	- 001011	DA	- 001025	EX	- 000013
- FW	- 001007	F0	- 001016	F1	- 001013	F2	- 001021
- I	- 001027	IE	- 000004	INX	- 000010	IW	- 000012
- K	- 001032	KDUMMY	- 001031	L	- 001030	LINMIN	- 000006
- LO	- 001014	L1	- 001015	L2	- 001020	NLN	- 001026
- NORM	- 001010	NPTS	- 000005	NVAR	- 000007	PHI	- 000002
- PHI	- 000003	R0	- 001012	R1	- 001017	R2	- 001022
- R3	- 001023	R4	- 001024	WTS	- 000001	Y	- 000000

START OF CONSTANTS

000720

START OF TEMPORARIES

000742

START OF INDIRECTS

001001

UNUSED COMPILER SPACE

037600

SUBROUTINE SOLVER(A,B,DB,IE,JD,N,NR,IFL,D1,02)

C SOLVER IS A ROUTINE TO SOLVE A*DB = B : A AND B ARE SYM.
 C B IS POSITIVE DEFINITE.

C REAL A(IE,1),B(JD,1),DB(JD,1)*X,01

```

000015      INTEGER D2
000015      IFL = 0
000016      NP1 = N + 1
000020      D1 = 1.0
000021      D2 = 0
000022      DO 70 I=1,N
000024      DO 70 J=1,N
000025      X = A(I,J)
000031      K = I-1
000033      10      IF (K.LT.1) GO TO 20
000036      X = X-A(I,K)*A(J,K)
000046      K = K-1
000050      GO TO 10
000050      20      CONTINUE
000050      IF (I.NE.J) GO TO 60
000052      D1 = D1*X
000054      IF (X.EQ.0.0) GO TO 140
000055      30      IF (ABS(D1).LT.1.0) GO TO 40
000061      D1 = D1*.0625
000062      D2 = D2*.4
000064      GO TO 30
000065      40      IF (ABS(D1).GE..0625) GO TO 50
000071      D1 = D1*.16.0
000072      D2 = D2*.4
000074      GO TO 40
000075      50      IF ((X.LT.0.0) GO TO 150
000077      A(NP1,I) = 1.0/SQRT(X)
000111      GO TO 70
000112      60      A(J,I) = X*A(NP1,I)
000122      70      CONTINUE
000127      DO 130 J=1,NR
000130      00 90 I=1,N
000131      X = B(I,J)
000136      K = I-1
000140      80      IF (K.LT.1) GO TO 90
000143      X = X-A(I,K)*DB(K,J)
000154      K=K-1
000155      GO TO 80

```

```
000156      90      DB(I,J) = X*A(NP1,I)
000171      I = N
000171      100      IF (I.LT.1) GO TO 130
000174      X = DB(I,J)
000200      K = I+1
000202      110      IF (K.GT.N) GO TO 120
000205      X = X-A(K,I)*DB(K,J)
000215      K = K+1
000216      GO TO 110
000217      120      DB(I,J) = X*A(NP1,I)
000230      I = I-1
000231      GO TO 100
000231      130  CONTINUE
000234      RETURN
000234      140  D1 = 0.0
000235      150  IFL = 1
000237      RETURN
000237      END
```

SOLVER	
SUBPROGRAM LENGTH	000261
FUNCTION ASSIGNMENTS	
STATEMENT ASSIGNMENTS	
10	- 000033 20 - 000050 30 - 000055 40 - 000065
50	- 000075 60 - 000112 70 - 000122 80 - 000140
90	- 000156 100 - 000171 110 - 000202 120 - 000217
130	- 000231 140 - 000234 150 - 000235
BLOCK NAMES AND LENGTHS	
VARIABLE ASSIGNMENTS	
I	- 000003 I - 000256 IFL - 000001
J	- 000257 K - 000260 NP1 - 000255 NR - 000000
X	- 000254
START OF CONSTANTS	
000241	
START OF TEMPORARIES	
000246	
START OF INDIRECTS	
000252	
UNUSED COMPILER SPACE	
041500	

SUBROUTINE INVRTA(N,A,IE,IFL)

ON RETURN A HAS THE LOWER TRIANGULAR PORTION OF I=A-VERSE STOR AS FOLLOWS (FOR N = 3) :

```

C     AAA
C     IAA
C     IIA
C     III
C     C

C     REAL A(I,J),X,Y,Z
000007   IF L = 0
000007   DO 40 I=1,N
000011   I1 = I+1
000013   DO 40 J=1,N
000014   J1 = J+1
000016   X = A(I,J)
000022   K = I-1
000024   10   IF (K.LT.1) GO TO 20
000027   X = X-A(J1,K)*A(I1,K)
000037   K = K-1
000040   GO TO 10
000041   20   IF (J.NE.I) GO TO 30
000043   IF (X.LE.0.0) GO TO 90
000045   Y = 1.0*SQRT(X)
000050   A(I1,I) = Y
000057   GO TO 40
000057   30   A(J1,I) = X*Y
000065   40 CONTINUE
000072   NL = N-1
000074   DO 60 I=1,NL
000075   KL = I+1
000077   DO 60 J=KL,N
000101   Z = 0.0
000102   J1 = J+1
000104   K = J-1
000105   50   IF (K.LT.1) GO TO -60
000110   Z = Z-A(J1,K)*A(K+1,I)
000120   K = K-1
000122   GO TO 50
000122   60   A(J1,I) = Z*A(J1,I)
000137   J1 = N+1
000141   DO 80 I=1,N
000142   DO 80 J=I,N

```

```
000143      Z = 0.0
000144      KL = J+1
000146      DO 70 K=KL,J1
000147      70      Z = Z+A(K,J)*A(K,I)
000163      80      A(KL,I) = Z
000174      RETURN
000174      90      IFL = 1
000175      RETURN
000176      END
```

INVRTA

SUBPROGRAM LENGTH
000224

FUNCTION ASSIGNMENTS

STATEMENT ASSIGNMENTS

10	-	000024	20	-	000041	30	-	000057	40	-	000065
50	-	000105	60	-	000122	70	-	000147	90	-	000174

BLOCK NAMES AND LENGTHS

VARIABLE ASSIGNMENTS

I	-	000215	I1	-	000216	J	-	000217	J1	-	000220
K	-	000221	KL	-	000223	NL	-	000222	X	-	000212
Y	-	000213	Z	-	000214						

START OF CONSTANTS

000200

START OF TEMPORARIES

000203

START OF INDIRECTS

000207

UNUSED COMPTLER SPACE

041700

NPAR	NVAR	NPTS	MAXITR	IW	LINMIN	EP	DAC
11	11	*0	10	0	10	1.0000E-05	5.0000E-02

OPTIMAL POINT REACHED IN 8 ITERATIONS

•15515072	•98462950	6.43276013	6.97716836	-6.16625657	•43606629
-----------	-----------	------------	------------	-------------	-----------

ERROR DATA OUTPUT SPECIFIED FIELD WIDTH ZERO* FORMAT NO.12100
- ERROR NUMBER 0071 DETECTED BY KODER AT ADDRESS 020131
CALLED FROM OUTPTC AT 020331
CALLED FROM AT 012012

ERROR SUMMARY

ERROR	TIMES
0071	0001

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